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Utilizing GRACE TWS, NDVI, and Precipitation for Drought Identification and Classification in Texas

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Utilizing GRACE TWS, NDVI, and Precipitation for Drought Identification and Classification in Texas

by

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by

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Drought is one of the most widespread and least understood natural phenomena. Many indices using multiple data types have been created, and their success at identifying periods of extreme wetness and dryness has been well documented. In recent years, researchers have begun to assess the potential of total water storage (TWS) anomalies in drought monitoring methodologies. The Gravity Recovery and Climate Experiment (GRACE) provides temporally and spatially consistent TWS measurements across the globe, and studies have shown GRACE TWS anomalies are suited to identify drought.

GRACE TWS is used with MODIS-derived normalized difference vegetation index (NDVI) and NOAA/NWS precipitation data to create a new drought index, the Merged-dataset Drought Index (MDI). Each dataset correlates with a different type of drought, giving robustness to MDI. MDI is based on dataset deviations from a monthly climatology and is objective and easy to calculate. MDI is studied across Texas, which is broken into five dataset-defined sub-regions. Multiple drought events are identified from 2002 - 2014, with the most severe beginning in October 2010. A new drought severity classification scheme is proposed based on MDI, and it is organized to match the current US Drought Monitor Classification Scheme.

MDI shows strong correlation with existing drought indices, notably the Palmer Drought Severity Index (PDSI). MDI consistently identifies droughts in different sub-regions of Texas, but shows better performance in regions with large GRACE TWS signals. MDI performance is enhanced through a weighting scheme that relies more on GRACE TWS. Even with this scheme, MDI and PDSI exhibit occasional behavioral differences.

Drought analysis using MDI shows for the first time that GRACE data provides information on a sub-regional scale in Texas, an area with low signal amplitudes. Past studies have shown TWS capable of identifying drought, but MDI is the first index to quantitatively use GRACE TWS in a manner consistent with current practices of identifying drought. MDI also establishes a framework for a future, completely remote-sensing based index that can enable temporally and spatially consistent drought identification across the globe. This study is useful as well for establishing a baseline for the necessary spatial resolution required from future geodetic space missions for use in drought identification at smaller scales.

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Chapter 1

Introduction

1.1 Motivation

Drought is one the most widespread natural phenomena, but it remains one of the most challenging to understand and represent. The complicated relationships between the components of the water cycle and the land surface-atmospheric interactions make it difficult to model and predict drought. One of the primary difficulties is the inconsistency of in-situ measurements available for drought monitoring; the measurements are not available everywhere (i.e. not spatially consistent), nor do they have continuous data records (i.e. not temporally consistent). Furthermore, droughts can be the result of water supply deficiencies in many different sources–surface water, ground water, soil moisture, etc. Measuring each of these components independently and then integrating them into a total water storage measurement is difficult to do consistently and accurately. For this reason, the measurements from the Gravity Recovery and Climate Experiment (GRACE) mission are extremely valuable.

The end-products from GRACE can be interpreted as total water storage (TWS) anomalies, which consider the variations in the entire amount of water present in a designated region (typically 1° grids). GRACE TWS anomalies include groundwater, surface water, and soil moisture, as well as snowpack anomalies in appropriate areas. GRACE's ability to provide measurements consistently in both space and time makes its TWS measurements a useful dataset for drought monitoring.

Historically, other datasets used in drought monitoring applications have included temperature, precipitation, evaporation, transpiration, vegetation etc. Because GRACE TWS is a relatively young dataset, and new to hydrologists in particular, few have implemented it into drought index calculations. Drought indices are values that represent the moisture level for a particular area. They utilize various water supply indicators including rainfall, snowpack, and streamflow and consider evaporation and transpiration. The cumulative effect of these values are assimilated in various ways to define moisture depletion. Previous studies have worked to assimilate GRACE TWS into land surface models, and assess drought conditions based on the model outputs [63], but few have worked to identify drought directly from GRACE TWS data.

Long et al. (2013) proposed using GRACE TWS measurements as an alternative to in-situ measurements for drought identification in Texas, and argued that TWS changes provide a more reliable indicator of water storage changes than disaggregated soil moisture and groundwater storage information [28]. Yirdaw et al. concluded that GRACE TWS is a reliable total water storage indicator that can be used for drought studies in the Canadian Prairie [61]. Chen et al. found GRACE TWS was useful in identifying drought in the Amazon River basin, and in particular, more accurately measured drought intensity as compared to climate and land-surface models that historically underestimate the intensity [11]. Li et al. noted that GRACE TWS and NDVI correlate well, and both identify the same droughts, though GRACE TWS based droughts last longer than NDVI based droughts, partly due to vegetation senescence [27]. Li also noted that GRACE TWS was particularly valuable for its ability to give information below the surface [27]. While these studies found GRACE TWS to be a reliable drought indicator, none developed a method to quantitatively define drought based on GRACE TWS measurements. Previous studies described methods to integrate GRACE TWS measurements into Land Data Assimilation Systems, such as NLDAS, and use the resulting information to identify droughts, but this integration can be difficult and time-consuming.

In the course of this research, Thomas et al. (2014) published a study describing a GRACE TWS-based quantitative method to measure the occurrence and severity of hydrological drought. This study used GRACE TWS deficits to quantitatively identify drought onset, duration, and severity and matched GRACE TWS-identified events to known meteorological droughts [51]. The authors investigated multiple regions, including Texas, and found GRACE TWS-identified events to accurately portray prolonged hydrological deficits and concluded GRACE TWS is a valid measurement to identify drought [51].

To more effectively use GRACE TWS to identify drought, a quantitative index should be developed. The Merged-dataset Drought Index (MDI) developed in this study merges GRACE TWS with vegetation and precipitation information to develop a robust index that quantitatively identifies drought. This study also proposes a new classification system to enable MDI interpretation in a framework consistent with current practices. By focusing specifically on Texas, ancillary information such as ecology and geography are also used to enhance and refine the analysis.

1.2 Objective

This study targets drought monitoring applications in the state of Texas. The Office of the State Climatologist hosts meetings of the Texas Drought Monitor Team, a group of individuals that use a variety of data types to assess drought conditions across Texas (`http://www.climatexas.tamu.edu`). A new quantitative index considering GRACE TWS, normalized difference vegetation index (NDVI), and precipitation data can improve this assessment. The selected datasets correlate with three types of drought, giving robustness to the MDI.

The MDI is the result of an effort to create an index that quantitatively uses GRACE TWS for drought identification. Established drought indices provide meaningful information for Texas, but an objective, transparent index was desired. MDI is based on dataset z-scores, so it is calculable independent of spatial geography, easy to understand, and easy to calculate anywhere data is available. This simplicity is a benefit. A classification scheme further enables comparison of MDI values from month to month, and a scheme designed to be compatible with the US Drought Monitor Classification Scheme enables MDI comparison with current drought indices.

An important aspect of MDI evaluation is understanding the ecological differences of the region of interest and accounting for those differences. There are many ways to organize the state into different sub-regions–by climate type, precipitation gradient, vegetation cover etc. A common organizational scheme used by climatologists are climatic divisions, which are organized by county. These political boundaries are less sensitive to natural ecological differences, however, so this organization scheme was not used. Instead, an ecological approach designed by the Environmental Protection Association (EPA) was used.

The EPA classifies North America into various levels of ecological regions, where Level I is the coarsest and Level IV is the finest. These ecological regions are defined by similarities in ecosystems and type, quality, and quantity of environmental resources [57]. Level I regions are broken into finer Level II regions that show more detailed ecological differences. Level II regions are further subdivided into Level III regions that map even more detailed ecological differences [13]. These regions are smaller, and thus allow more local definition. Texas comprises two Level I regions, five Level II regions, and 12 Level III regions. The Level III map of Texas is provided in Figure 1.1. The numerical value associated with each region is an EPA designation. Region 23, or the Arizona/New Mexico Mountains, is aggregated into the Chihuahuan Desert before any processing is performed because of its small spatial area. Each dataset is initially organized by these Level III region designations.

Figure 1.1: Texas Level III Ecoregion Designations

Vegetation and precipitation in Texas follow an east-west gradient. The eastern part of the state (South Central Plains, East Central Texas Plains, Blackland Prairies, Western Gulf Coastal Plains) receives the most precipitation and has abundant vegetation. Central Texas (Cross Timbers, Central Great Plains, Edwards Plateau, Southern Texas Plains) is drier and more sparsely vegetated. West Texas (Chihuahuan Desert, High Plains, Southwestern Tablelands) receives limited precipitation and has little vegetation. Thus, there are significant differences in geology, physiography, climate, soils, vegetation, land use, and hydrology from ecoregion to ecoregion.

Additionally, Texas is underlain by nine major aquifers. They are different types and have a variety of responses to water changes. The Ogallala aquifer lies underneath most of the High Plains, but it is a slow-responding aquifer. Conversely, Edward's aquifer lies underneath Edwards Plateau and is a fast-responding aquifer. The aquifer type and its reaction to precipitation events can significantly impact vegetation as well as total water storage. MDI is designed to consider these differences. The datasets are standardized such that an index value of +1 in East Texas is equivalent to a value of +1 in West Texas.

1.3 Datasets

This index is limited by the spatial and temporal availability of its comprised datasets. The GRACE TWS dataset, while representing an improvement in temporal scale over previous global gravity maps, is still relatively spatially and temporally coarse (500 km and monthly resolution, respectively). Other data used to construct this index are available at finer spatial (NDVI is available at 250 m and precipitation at 8 km) and temporal (NDVI available bimonthly) resolutions.

Each dataset is chosen because it correlates to a different part of the hydrological cycle. GRACE TWS measures water storage and quantifies the risk for and recovery capacity from drought. NDVI measures photosynthetic activity, which is used to assess vegetation health. Removing seasonal effects, vegetation health represents the volume of readily available water. Precipitation is slightly different as it is an input to the water cycle as opposed to a measure of what is available. Additionally, each dataset measures a different type of drought. Short-term meteorological drought is best measured by rapidly (weekly) changing variables like precipitation. Longer lasting agricultural drought is best measured by variables changing on a monthly basis like vegetation. Long-term hydrological drought is best measured by slowly (multi-month) changing variables like GRACE TWS. These types of drought do not occur independently, and it is important to account for their interaction. The inclusion of measurements of with various time scales achieves that.

1.3.1 GRACE TWS

The Gravity Recovery and Climate Experiment (GRACE) is a joint National Aeronautic and Space Administration (NASA) and Deutsches Zentrum fur Luft und Raumfahrt (DLR) scientific mission. It aimed to provide global coverage of the Earth's gravity field from a single source, which had not been previously accomplished [5]. It is currently in its 12$^{\text{th}}$ year of operation, and has provided monthly gravity field maps for the globe since its launch in March 2002. These gravity maps provide unprecedented estimates of gravity anomalies on global scales, as well as ensuring temporal consistency, which is traditionally a problem with many in-situ measurements. GRACE's design spatial resolution is 400 km. It is comprised of twin satellites in near circular, near polar orbit at an altitude of 500 km and a nominal separation of 220 km [5].

GRACE does not measure gravity anomalies directly. It instead measures the instantaneous range change between the two satellites using K/Ka-band ranging (KBR) [12]. As mass moves around Earth's surface, the geopotential of the Earth experiences small changes, forcing the satellite range to alter. Accounting for mass movement in the atmosphere and other variability, the remaining mass movement over land is attributed to water movement. One of the GRACE products is terrestrial water storage (TWS) anomalies at monthly time intervals over the globe. TWS accounts for water stored in the soil and ground water reservoirs, snow, and accumulated precipitation, evapotranspiration, and surface and subsurface runoff within a given area. With the ability to monitor water movement through the hydrological cycle, TWS change is a good indicator of abnormal climatic events, such as drought [11]. In particular, GRACE TWS is a valuable tool for studying hydrological drought, a type of long-term drought [26].

GRACE is able to very precisely measure the range changes, but the information it provides is band-limited (i.e., there is a minimum signal amplitude it can observe). Traditionally, the larger the area of interest, the smaller the signal amplitude can be for detection; conversely, for a smaller area of interest, a larger signal amplitude is required. Many studies have been performed on global and continental scales, where smaller signals are visible. Additionally, many studies have been performed for smaller areas, such as individual ice sheets, that exhibit large signals such as the melting of ice sheets. Chen et al.

(2008) used GRACE to determine an ice sheet with an area of 10% of Texas sustained a 28.8 km^3 loss [10]. Additionally, GRACE has been used to detect changes in gravity due to seismic events such as the Tohoku-Oki [3, 37, 29], Central Chile [16, 20], and Sumatra-Andaman earthquakes [17]. Few studies have been conducted for small geographical areas with small signal amplitudes, but this study helps fill that void.

1.3.2 Normalized Difference Vegetation Index (NDVI)

Drought indices can be based on ground or satellite measurements. Droughts typically affect vegetation state and cover, so vegetation indices (VIs) comprised of information from multispectral bands are commonly used in drought detection [55]. The normalized difference vegetation index (NDVI) is the most commonly used vegetation index [24] and is based on differences in absorption and reflectance in the visible and near-infrared (VNIR) spectrums, respectively. NDVI can identify drought in semirarid and arid lands [55] as well as in more heavily vegetated lands such as the Great Plains [22]. Additionally, NDVI is a VNIR index, and this class of indices is more reliable than other types of indices at evaluating the vegetation condition over intermediate vegetation coverage levels [21].

For this study, NDVI serves as a more rapid indicator of drought than GRACE TWS, making NDVI well-suited for measuring agricultural drought. Vegetation is an indicator of the level of photosynthetic activity in a region, and a decrease in activity points to deficiencies in water resources. Vegetation represents the health of a region and provides a measure of immediately available water.

1.3.3 Precipitation

Precipitation has the most apparent connection to drought. Deficiencies in precipitation trigger meteorological drought, which can become agricultural or hydrological drought with sustained water inadequacies. This study uses in-situ precipitation data. The PRISM Climate Group, part of the Northwest Alliance for Computational Science and Engineering based at Oregon State University, produces precipitation maps for the United States and utilizes observations from 1895 - present. The monthly datasets PRISM produces are an aggregation of precipitation data, and are less noisy than daily precipitation values.

While GRACE TWS and NDVI measure longer-lasting drought events, precipitation can have an immediate impact on a region and inflict changes on a short-term scale. Precipitation is considered as an input to the hydrological cycle, while GRACE TWS and NDVI measure the severity of water deficiencies.

1.4 Thesis Organization

The remaining sections of this document are as follows. Chapter 2 expands on each dataset's relevance to the study and provides extensive background for each dataset being used. Chapter 3 outlines the data processing methods used to divide the region of interest into appropriate sub-regions that are used in the drought index study. Chapter 4 provides extensive background on drought types and existing indices. It discusses the creation of the Multi-dataset Drought Index (MDI), the development of the drought classification scheme, and identified droughts in the region of interest. Chapter 5 discusses nuances of the index, and analyzes selected drought events in detail. Chapter 6 concludes the study and makes future recommendations.

Chapter 2

Data Selection

Each dataset used in this study was selected for its ability to identify water changes. GRACE TWS directly quantifies surface and subsurface water storage, and precipitation directly measures the incoming amount of rainfall and/or snow. Vegetation is an indirect measurement of water abundance. GRACE TWS is the least mature dataset and is available beginning April 2002. Consequently, this study spans April 2002 to January 2014.

2.1 Total Water Storage

Earth's gravity field is a non-uniform and time-varying entity. This non-uniformity creates small forces that the GRACE satellites interpret as small accelerations. Due to the along-track separation of the satellites, each experiences a slightly different acceleration resulting in a continuously varying inter-satellite range. GRACE utilizes a K/Ka-band ranging system (KBR) [12] to measure these ranges to the micron level [50]. The gravitational forces are not the only forces contributing to the inter-satellite range, so additional measurements are required to isolate the contribution from Earth's gravity field. SuperSTAR accelerometers are used to measure non-gravitational forces acting on the satellite [54], and Blackjack GPS receivers provide relative and absolute timing for the data [62].

The Level 1 inter-satellite range data [8] are used in least-squares analysis with GPS tracking information, satellite altitude data, and accelerometer measurements, that are then combined with models to estimate the Earth's gravitational potential. The potential is then expressed as Level 2 spherical harmonics (Level 2 data) [4]. QR factorization is also used to generate the coefficients. From the geopotential coefficients series, a mean is calculated and removed. This isolates the time-varying contribution and allows changes in the geoid (Earth's surface) to be determined. Procedures outlined in Wahr et al. are used to find the change in surface mass, which is expressed as total water storage (TWS) anomalies [56].

The harmonics used to calculate TWS anomalies are generated to degree and order 120, and this finite range introduces spatial leakage problems [11]. After the harmonics are generated, smoothing is performed to reduce the contribution of the noisy short-wavelength components. Additionally, stripe errors in the solution can completely mask the signal. These errors can be removed using a variety of techniques, notably "de-striping" [47] and Gaussian smoothing [56]. This smoothing, however, creates signal leakage between areas and also attenuates the signal [47]. The signal attenuation can be reversed to a degree by using scaling factors that are dependent on the area of the region [48].

The data used in this study is regularized. To mitigate the striping errors, the gravity field is stabilized by utilizing a degree- and order-dependent regularization matrix. This matrix is designed using knowledge of the characteristic errors in the CSR RL04 GRACE solutions and is computed for every monthly solution to reduce errors [44]. The regularized GRACE solutions show less error compared to the unconstrained solutions, even without any Gaussian smoothing [44]. This improves the higher-degree harmonic coefficients, resulting in enhanced signal retention at fine spatial resolutions.

Improved signal retention impacts drought monitoring applications because historical datasets used to monitor drought conditions have spatial resolutions on the order of tens of kilometers. A deficiency of historical datasets, however, is their inability to consistently measure subsurface water storage. Long-lasting droughts are known as hydrological droughts and are characterized by deficiencies in surface and subsurface water supply. Leblanc noted "the only way to properly assess the impact of a drought on water resources is through an integrated measure of all water storage types" [26]. GRACE TWS provides this water storage measurement consistently and accurately, making it uniquely suited to study hydrological drought.

2.2 Normalized Difference Vegetation Index

NDVI is one of many vegetation indices used around the world. NDVI is constructed using multispectral data measured by the Moderate Resolution Imaging Spectroradiometer (MODIS), an instrument aboard the Terra and Aqua satellites (part of the Earth Observing System mission) [34]. MODIS provides global data in 36 spectral bands every two days. Additionally, the data is available at three spatial resolutions. The finest resolution is 250 m, consisting of visible red and near-infrared (NIR) spectral bands designed specifically to measure NDVI. NDVI is a measure of the photosynthetically active vegetation in a given area. Leaf cells in plants scatter light in the near-infrared range (700-1100 nm) because the light does not have enough energy for photosynthesis. Conversely, plants use photosynthetically active radiation (PAR), which is in the visible range (400-700 nm), for photosynthesis. Plants are thus dark in visible light and bright in infrared light. NDVI is a unitless quantity between -1 and +1, and is calculated according to equation 2.1, where ρ is reflectance in the respective spectral band. In this equation, the sum and difference of the two bands are used to adjust for the effects of solar zenith angle [45].

$$NDVI = \frac{\rho_{NIR} - \rho_{VIS}}{\rho_{NIR} + \rho_{VIS}} \tag{2.1}$$

Theoretically, pixels with vegetation have values ranging from +0.2 to +1.0. In actuality, MODIS measurements will rarely exceed 0.8 to 0.9. More reflected radiation in near-infrared means there are more leaves, and consequently more vegetation, which results in a larger NDVI value. In an area expected to be densely vegetated, a low NDVI value is indicative of vegetation stress, which can be due to numerous factors, including drought.

Different particles may interfere with light measurements and consequently impact NDVI. Clouds, water vapor, and aerosols can affect the measurements and must be considered. Additionally, water in the soil may change the spectral response and artificially modify the NDVI value. The data used in this study implements multiple corrections. At the satellite, atmospheric corrections are made for the Rayleigh effect and aerosols. NASA uses algorithms to select nadir views, remove cloudy days, and perform quality checks, one of which is based on elevation and solar angle. At the University of Texas, scientists perform additional quality checks to verify NASA's results before the NDVI data is used [46].

Vegetation is a good rapid-response indicator to water stress because it measures the level of photosynthetic activity. While hydrological drought is a long-lasting drought, agricultural drought is a mid-term drought that occurs more quickly. Vegetation health is an indicator of accessible water and gives a measure for the overall health of the ecosystem. NDVI is particularly well suited to drought monitoring applications because it is a VNIR-based index, and these types of indices are particularly good at monitoring vegetation dynamics for intermediate levels of vegetation cover, typically found in Texas [21]. Additionally, Texas comprises multiple ecosystems ranging from desert to plains to coniferous forest, and NDVI has been shown to identify vegetation coverage and stress in these types of environments [55, 22].

2.3 Precipitation

Precipitation data used in this study is delivered by the PRISM Climate Group at Oregon State University. Their rainfall maps are based on measurements gathered from a variety of stations across North America. This dataset is different from the other two as it is ground-based as opposed to satellite-based. These precipitation datasets are produced monthly, beginning in 1895 and are available from `http://prism.oregonstate.edu`. These datasets are modeled using climatologically-aided interpolation, which is a method that uses the long-term average as the predictor grid.

Precipitation is different from the other two datasets because it can be considered an input to a system while vegetation and TWS measure responses. This is an important distinction. Precipitation is also unique because it is such a rapidly changing variable. Heavy precipitation can make a nearly immediate impact on surface water levels, while water changes do not manifest themselves in vegetation for weeks and may not ever change subsurface water supply. The short-term rapid influence of precipitation is important for monitoring short-term meteorological drought, which is the third type of drought.

2.4 Dataset Relationships

Incorporating datasets that reflect different types of drought is important for developing a drought index capable of identifying events having varying time scales. Hydrological drought can persist even through abundant rainfall if the precipitation is unable to impact the subsurface water storage [26], and GRACE TWS accounts for this. GRACE TWS also reflects that groundwater systems typically take longer to recharge. Conversely, an index should also be able to account for periods of excessive or insufficient moisture even if a region is already in drought, which precipitation accounts for. To consider timescales between those measured by GRACE TWS and precipitation, NDVI is included. Vegetation is another measure of system health that is not as rapidly changing as precipitation, which allows NDVI to retain some of the system's past history as a "pre-conditioning".

Evaluating the dataset relationships is complicated. Texas is a low-latitude (24° to 37° N), water-limited growth region [24]. This means the abundance of water is the limiting factor for vegetation growth, as opposed to the amount of energy available to a plant for photosynthesis. The datasets are expected to exhibit positive correlations; a surplus of water (either as TWS or precipitation) will cause an increase in vegetation. These relationships are complicated, however, by the time delay, or lag, among them. Precipitation, for example, more immediately impacts vegetation than it does TWS, and depending on the dryness of the region, precipitation may never change TWS. Additionally, whether or not a region overlays an aquifer (and the aquifer type) influences GRACE TWS response.

Chapter 3

Dataset Organization Methods and Results

This chapter details the methods used to organize the region of interest. Texas is initially split into 11 Level III ecoregions. This scheme, however, is not compatible with the GRACE TWS dataset because the spatial resolution of the scheme is too fine. A method was needed to aggregate the ecoregions into "super-regions" that were compatible with the GRACE TWS data. Once this aggregation was complete, it was tested with the other datasets to ensure their compatibility. The final organization scheme was then selected and used for the drought analysis discussed in Chapter 4 and Chapter 5.

3.1 Correlation Study

The datasets have various spatial and temporal scales and must be converted to a unified scale. GRACE TWS limits both the spatial and temporal resolution. While the GRACE TWS grids are produced at 1° intervals, the values cannot be used at this fine a resolution [41]. Instead, the values need to be averaged over a region defined by some smoothing radius. The minimum smoothing radius is 220 km, creating a basin area of 150,000 km^2 [42, 63]. For smaller areas, the noise in the data begins to overwhelm the signal [42]. It is important to note, however, that the minimum area can vary with respect to signal amplitude. Studies dealing with ice mass loss for example, work with areas in the tens of thousands of kilometers and signals with amplitudes over 20 km^3 [10]. Texas, however, is not expected to have extremely large signals, so an area of 150,000 km^2 is appropriate. The state of Texas is approximately 700,00 km^2, so 5 divisions would be expected.

The purpose of the correlation study was to analyze the relationships among the 11 ecoregions and determine the optimal organization scheme. GRACE TWS is a global dataset, but past studies have evaluated Texas as one region [28, 51]. This correlation study is a way to demonstrate that GRACE TWS data provides information on a sub-regional scale in Texas.

3.1.1 Pre-processing

Data analysis is performed using MATLAB. Prior to this, the datasets are processed in ArcGIS, a geographic information system used to create, compile, and analyze maps. It accepts multiple types of input, including rasters and vectors. Both the NDVI and precipitation datasets were available in forms readily compatible with ArcGIS. GRACE TWS datasets were not. To view the GRACE TWS gridded data in ArcGIS, a script developed by Arthur Ryzak at the Center for Research in Water Resources at the University of Texas at Austin was utilized. This script utilizes gridded datasets from the Center for Space Research (`www.csr.utexas.edu/grace/RL05.html`) and manipulates them into a format readable by ArcGIS [43]. Due to the coarse spatial resolution of the data, tools native to ArcGIS are not used to calculate dataset statistics such as mean, minimum and maximum for a desired region. Rather, the area of interest is clipped from the global map and saved as a GeoTIFF image compatible for post-processing in MATLAB. The GeoTIFF is imported to MATLAB and converted to a matrix, where each matrix value corresponds to a 1° pixel. Using the boundaries of the 11 Level III ecoregions, the author defined which GRACE TWS pixels (grid points) corresponded to which ecoregion. With these pixel groupings, regional statistics are calculated and used in methods described in Chapter 3.1.2. The pixel organization map is provided in Appendix A.

The other datasets, NDVI and precipitation, are natively compatible with ArcGIS. Once these datasets are in ArcGIS, the ArcGIS 'Calculate Zonal Statistics' tool is utilized to calculate regional statistics such as mean, minimum, maximum, standard deviation, and range. These statistics are calculated for every available month from April 2002 to January 2014 and are converted into spreadsheets that are compatible for post-processing in MATLAB. A script created by the author automated this process for the 145 months of data.

Seasonality must also be considered. The strength of annual cycles can mask other data trends and should be removed. To remove effects due to seasonality, a monthly climatology is calculated for each dataset (i.e. a January mean, a February mean etc.). Each month is then differenced from that monthly climatology. The resulting values are referred to as deviations (GRACE TWS deviations, NDVI deviations, and precipitation deviations). This standardizes the values each dataset represents such that they are all representative of anomalies. These deviations are the data used in this analysis.

Note the distinction of deviations from anomalies; GRACE TWS anomalies are generated by removing the mean static gravitational field, but the GRACE TWS deviations from the monthly climatology are used in this analysis. NDVI and precipitation deviations are self-explanatory.

3.1.2 Correlation Calculations

Texas comprises multiple distinct ecological regions. For the purposes of drought analysis, it was important to divide Texas into different "super-regions" that show distinct behavior from each other. GRACE TWS was the limiting dataset, so the analysis was first performed using GRACE TWS deviations.

Each of the 11 ecoregions was correlated with every other using the Pearson correlation coefficient, given in equation 3.1. Regions with high correlation are similar. Above a certain threshold, the similarity signifies that the regions are not distinct according to GRACE TWS deviations. These similar regions are then aggregated and the process repeated. After an organization scheme is created based on the GRACE TWS deviations, it was tested with NDVI and precipitation deviations.

$$r = \frac{\Sigma_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\Sigma_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\Sigma_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{3.1}$$

In addition to calculating the correlation coefficient, the spatial standard deviation of the GRACE TWS deviations was calculated for each region. The standard deviation is representative of the dataset noise and should not mask the signal variation. Signal variations themselves can be treated as "patterns" that can be used to identify regions with similar behavior and further corroborate the scheme devised by the correlation coefficient study. Once the regions of the state have been analyzed and aggregated, the final organization scheme was analyzed in terms of Pearson correlation coefficient, mean and standard deviation trends, and the "super-region" areas calculated.

3.2 Correlation Results

The analysis described in Chapter 3.1 was performed for each of the three datasets: GRACE TWS, NDVI, and precipitation. Recall that deviations from the seasonal climatology are used. The analysis began with the original 11 ecoregions, and the results drove the aggregation sequentially down to 5 regions. Intermediate organization schemes consisted of anywhere from 6 to 9 regions, but these still showed too much GRACE TWS deviation correlation. A scheme was devised based on the GRACE TWS results, and then supported with the other two datasets' results.

3.2.1 GRACE TWS

The spatial resolution of the GRACE TWS dataset is the limiting factor for aggregating areas in Texas. As shown in Figure 1.1, there are 11 Level III regions. This was an appropriate starting place to evaluate region correlation because finer areas would be too small to be discernibly differentiated by GRACE, but larger areas might aggregate disparate information.

Auto correlations (equation 3.1) for 11 Level III showed regions with very high ($\rho \geq 0.9$) correlation. The South Central Prairie, Blackland Prairie, and East Central Texas Plains in East Texas were highly correlated. In West Texas, the High Plains, Southwestern Tablelands, Edwards Plateau, and Central Great Plains demonstrated high correlation. Some regions showed high correlations with multiple areas, suggesting they would be a natural aggregation. Table 3.1 shows the correlation coefficients for the 11 Level III ecoregions. Table 3.2 relates ecoregion name and number.

Ecoregion	24	25	26	27	29	30	31	32	33	34	35
24	1										
25	0.81	1									
26	0.75	0.95	1								
27	0.76	0.89	0.94	1							
29	0.67	0.79	0.85	0.94	1						
30	0.84	0.84	0.86	0.93	0.88	1					
31	0.71	0.66	0.70	0.71	0.67	0.79	1				
32	0.60	0.71	0.80	0.88	0.96	0.82	0.63	1			
33	0.69	0.76	0.82	0.90	0.95	0.91	0.75	0.95	1		
34	0.62	0.65	0.68	0.74	0.79	0.80	0.83	0.77	0.89	1	
35	0.57	0.68	0.74	0.82	0.89	0.79	0.59	0.94	0.92	0.77	1

Table 3.1: Level III GRACE TWS Correlations

Ecoregion Number	Name
24	Chihuahuan Desert
25	High Plains
26	Southwestern Tablelands
27	Central Great Plains
29	Cross Timbers
30	Edwards Plateau
31	Southern Texas Plains
32	Blackland Prairie
33	East Central Texas Plains
34	West Gulf Coast Plain
35	South Central Texas Plains

Table 3.2: Ecoregion Names

Region aggregations were based on a critical ρ value. If two regions have a correlation above this critical value, it is a statistically significant correlation and the regions are aggregated. Table 3.3 gives these critical values for up to 12 points (note the values are based on degrees of freedom instead of sample size, n). The critical value used to determine statistical significance for 11 points is 0.74. As regions are aggregated, however, the sample size decreases and the critical value increases. For this reason, a critical value of 0.9 was used to determine statistically significant correlation.

The resulting scheme based on the GRACE TWS deviations was comprised of five super-regions as shown in Figure 3.4. The final configuration, including the region correlation coefficients, is presented in Chapter 3.2.4.

Degree of Freedom DF = n - 2	Significance Level
1	0.9999
2	0.990
3	0.959
4	0.917
5	0.874
6	0.834
7	0.798
8	0.765
9	0.735
10	0.708

Table 3.3: Critical Values of Pearson Correlation Coefficient

The behavior of the GRACE TWS deviations is shown for each of the original 11 ecoregions in Figure 3.1. The red line denotes the signal behavior, and the error bars are shown in blue. Across the state, all ecoregions agree in their identification of extreme deviations. Additionally, all ecoregions show that the signal noise does not mask the signal behavior, i.e. the spatial standard deviations do not exceed variations in signal value. Ecoregions in the eastern part of the state exhibit similar patterns to each other, which are distinct from the western part of the state. East Texas shows more variable behavior (Blackland Prairie, East Central Texas Plains, South Central Plains) as compared to West Texas (Chihuahuan Desert, South Texas Plains). This pattern similarity agrees with the results of the correlation coefficient study, validating the final organization scheme.

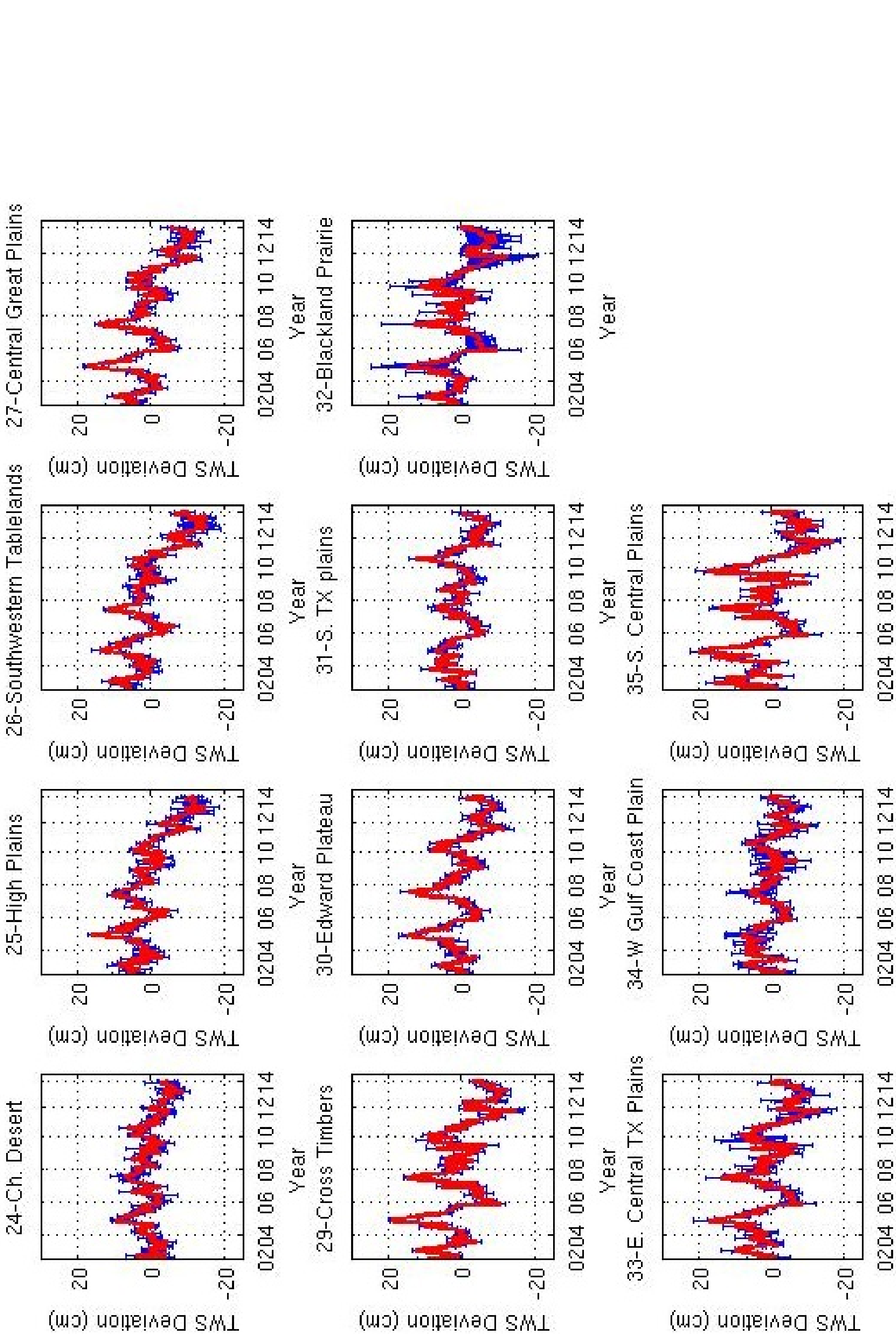

Figure 3.1: GRACE TWS Behavior (Level III Organization)

3.2.2 NDVI

Like the GRACE TWS data, NDVI deviation correlations for the 11 Level III regions showed regions with very high ($\rho \geq 0.9$) correlation. Table 3.4 provides these results. Compared to the GRACE TWS data, these regions show more diversity (i.e., fewer have such strong correlations). This is not surprising given the improved spatial resolution of the NDVI data.

Ecoregion	24	25	26	27	29	30	31	32	33	34	35
24	1										
25	0.88	1									
26	0.79	0.95	1								
27	0.57	0.76	0.85	1							
29	0.41	0.58	0.67	0.89	1						
30	0.68	0.78	0.81	0.88	0.82	1					
31	0.54	0.64	0.69	0.77	0.74	0.85	1				
32	0.29	0.44	0.52	0.77	0.92	0.71	0.70	1			
33	0.41	0.55	0.63	0.82	0.90	0.82	0.84	0.94	1		
34	0.47	0.54	0.58	0.62	0.65	0.71	0.85	0.69	0.82	1	
35	0.36	0.44	0.46	0.57	0.68	0.58	0.50	0.74	0.75	0.57	1

Table 3.4: Level III NDVI Correlations

The finer spatial resolution is also observed when the signal behavior is evaluated. Compared to the GRACE TWS results, fewer regions have such strong similarity.

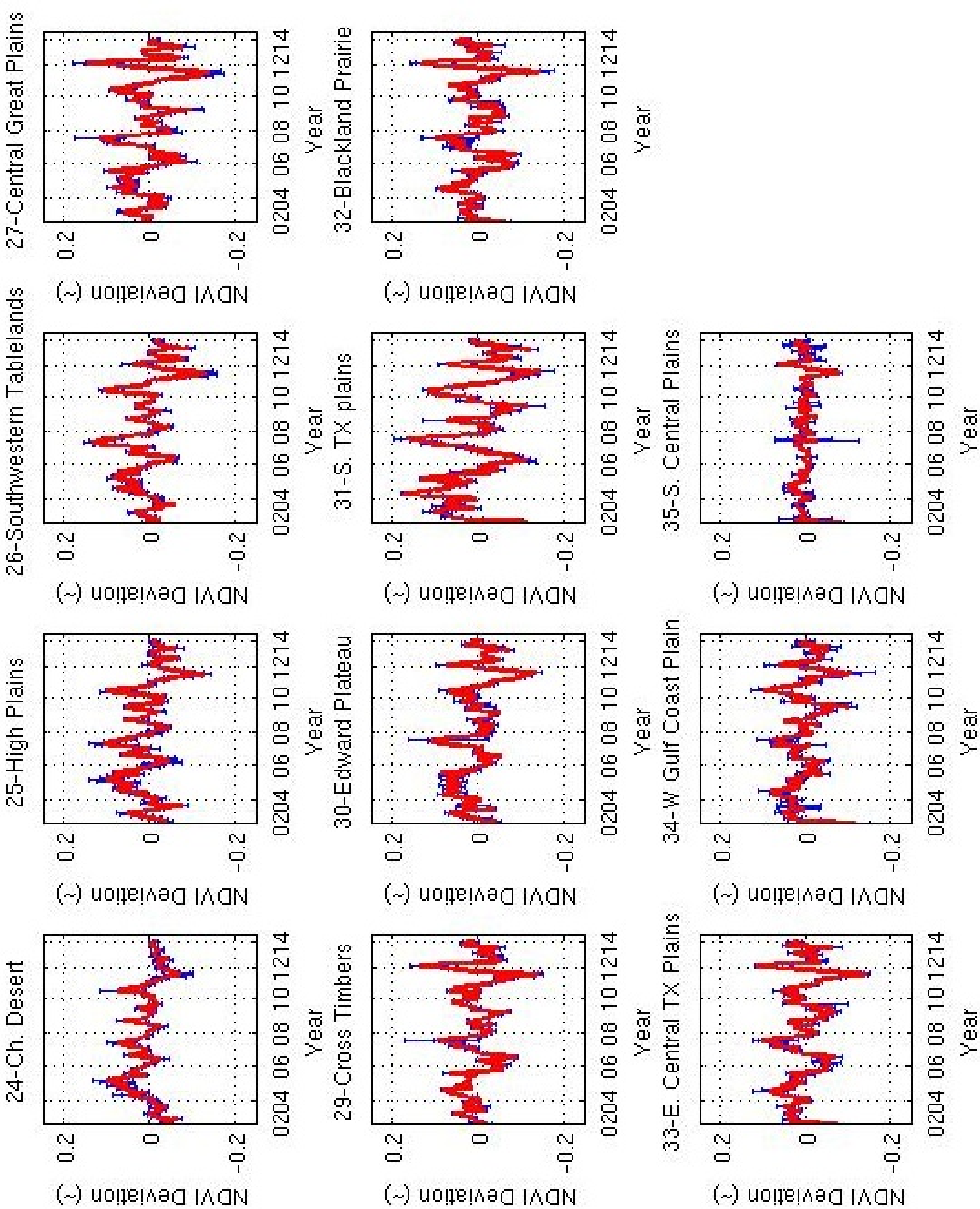

Figure 3.2: NDVI Behavior (Level III Organization)

3.2.3 Precipitation

Precipitation deviations exhibit very high correlations as well. Texas has a strong east-west precipitation gradient, so this is not surprising. Like NDVI, the precipitation spatial resolution is much finer than GRACE TWS, so more distinction among regions is retained. This is shown both through the correlation coefficient values and the signal behavior.

Ecoregion	24	25	26	27	29	30	31	32	33	34	35
24	1										
25	0.81	1									
26	0.70	0.92	1								
27	0.62	0.74	0.85	1							
29	0.45	0.51	0.60	0.84	1						
30	0.66	0.64	0.70	0.83	0.83	1					
31	0.50	0.41	0.46	0.52	0.60	0.78	1				
32	0.41	0.45	0.54	0.73	0.93	0.83	0.66	1			
33	0.42	0.44	0.52	0.66	0.83	0.83	0.73	0.96	1		
34	0.42	0.35	0.42	0.45	0.53	0.67	0.80	0.67	0.79	1	
35	0.31	0.33	0.42	0.51	0.65	0.60	0.48	0.81	0.87	0.69	1

Table 3.5: Level III Precipitation Correlations

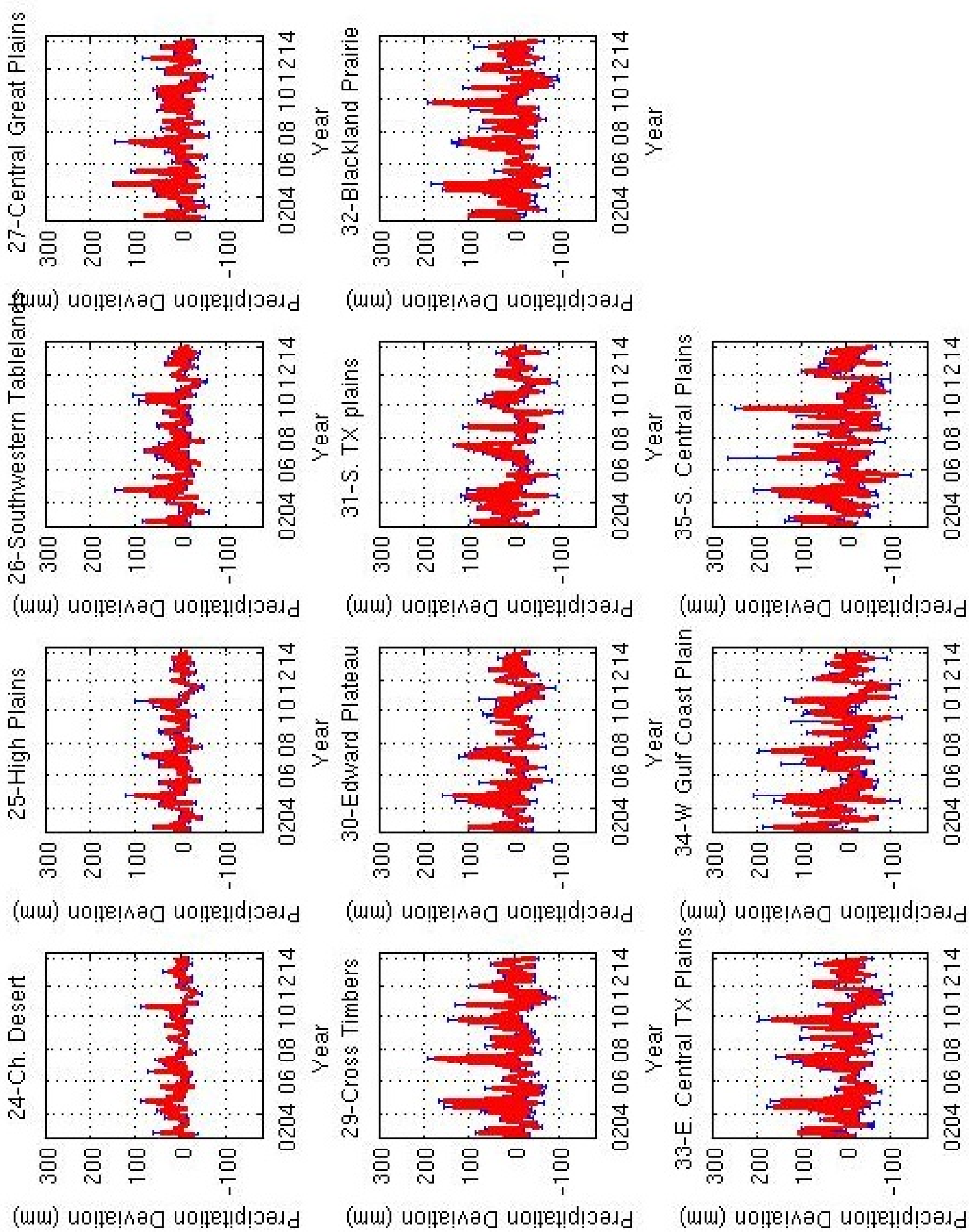

Figure 3.3: Precipitation Behavior (Level III Organization)

3.2.4 Final Organization

Considering the GRACE TWS deviation correlation study, an organization scheme comprising five super-regions was created. The correlation coefficients were calculated for these regions, and all values were below the cut-off level for statistical significance, demonstrating that each region was unique. The other datasets were aggregated in the same scheme, and the results of the correlation study validated the GRACE TWS-driven selection. Figure 3.4 shows the final organization scheme, and the correlation results are presented in Table 3.6 through Table 3.8. For the correlation coefficient results, the following abbreviations are used: CD = Chihuahuan Desert, HP = High Plains, CP = Central Prairies, STP = South Texas Plains, WGC = West Gulf Coast Plains. Future analysis considers this organization scheme.

Additionally, despite the spatial resolution disparities, each dataset identified the same region aggregations. For example, in all three datasets, the Southwestern Tablelands and High Plains show very high correlation ($\rho_{GRACETWS}$ = 0.95, ρ_{NDVI} = 0.95, ρ_{PRECIP} = 0.92), as do the East Central Texas Plains and the Blackland Prairie ($\rho_{GRACETWS}$ = 0.95, ρ_{NDVI} = 0.94, ρ_{PRECIP} = 0.96). While GRACE TWS is the limiting factor for aggregating areas, all the datasets exhibit similar behavior.

The scheme derived in this study is similar to the Level II organization scheme published by the EPA. They are different in that the Cross Timbers region is part of the High Plains region in the data-defined organization, whereas it is part of the Central Prairies in the Level II designation. This difference does not significantly impact the regional correlations, so the author-defined organization scheme is retained.

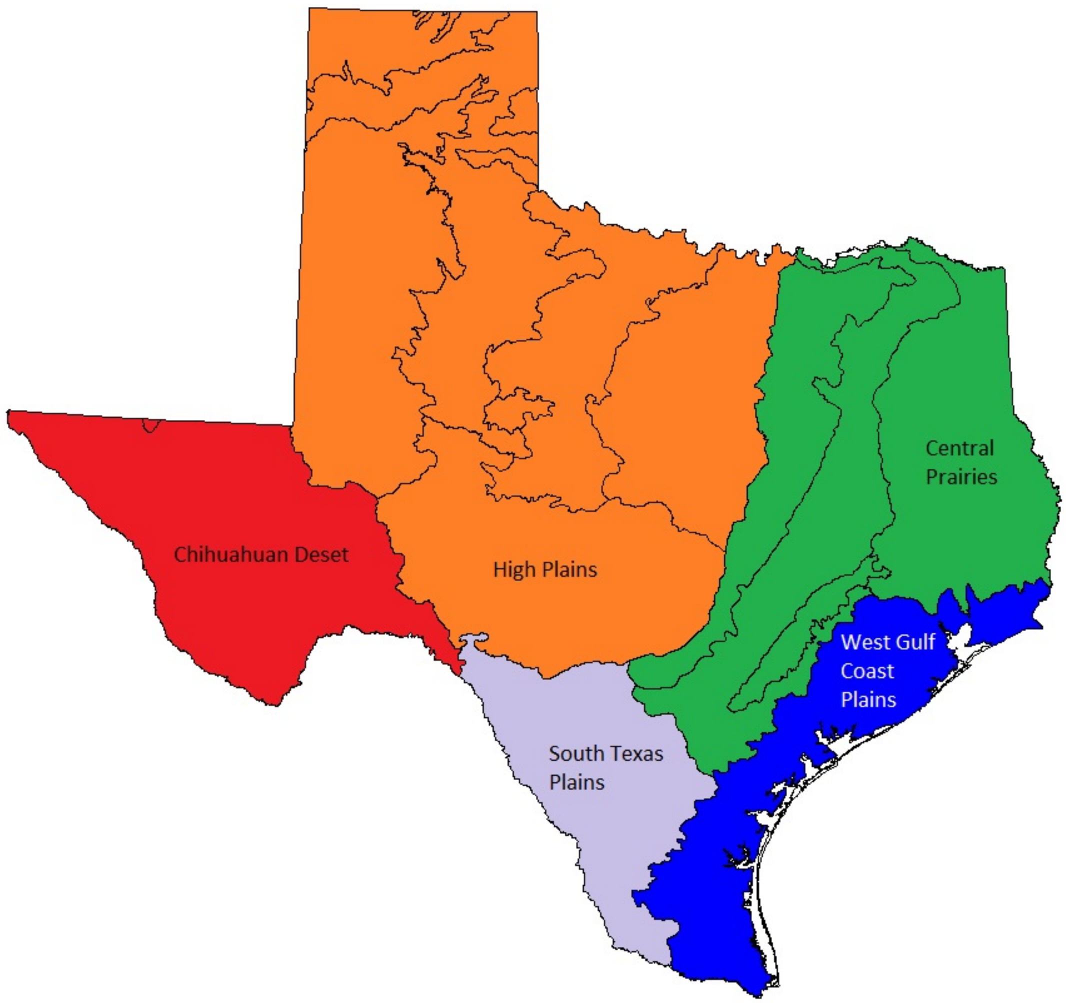

Figure 3.4: Final Organization Scheme

Ecoregion	CD	HP	CP	STP	WGC
CD	1				
HP	0.82	1			
CP	0.62	0.84	1		
STP	0.71	0.73	0.64	1	
WGC	0.62	0.75	0.81	0.83	1

Table 3.6: Super Region GRACE TWS Correlations

Ecoregion	CD	HP	CP	STP	WGC
CD	1				
HP	0.72	1			
CP	0.37	0.78	1		
STP	0.54	0.80	0.76	1	
WGC	0.47	0.68	0.76	0.85	1

Table 3.7: Super Region NDVI Correlations

Ecoregion	CD	HP	CP	STP	WGC
CD	1				
HP	0.69	1			
CP	0.36	0.74	1		
STP	0.50	0.65	0.63	1	
WGC	0.40	0.56	0.74	0.78	1

Table 3.8: Super Region Precipitation Correlations

The behavior of each dataset in the new scheme is shown in Figure 3.5 through Figure 3.7. For a particular dataset, the behavior still exhibits similarities across the state, but there are regional distinctions. The GRACE TWS deviation behavior, for example, shows clear differences between wet and dry parts of the state. The Central Prairies (wet) exhibit a wider range of values, while the Chihuahuan Desert (dry) has much less fluctuation. These are relative extremes for the state of Texas, but something more moderate like the High Plains is distinct as well.

Evaluating the NDVI deviation behavior, the Chihuahuan Desert again has the least variation (to be expected), but the South Texas Plains shows the most variation. While the Central Prairies consistently has more vegetation, it is a more stable environment (in terms of precipitation and temperature), so changes in vegetation are not as magnified. The South Texas Plains does not contain as much vegetation, the majority of which is mesquite. Evaluating the precipitation deviation behavior, the Chihuahaun Desert again has the least variation (it has the least rainfall of any region), and regions in East Texas (Central Prairies and the West Gulf Coast Plains) exhibit the most variation. Considering historic rainfall patterns across the state, this deviation distribution aligns with rainfall distribution across the state. Eastern Texas receives more rain for many reasons, including tropical storm landfall.

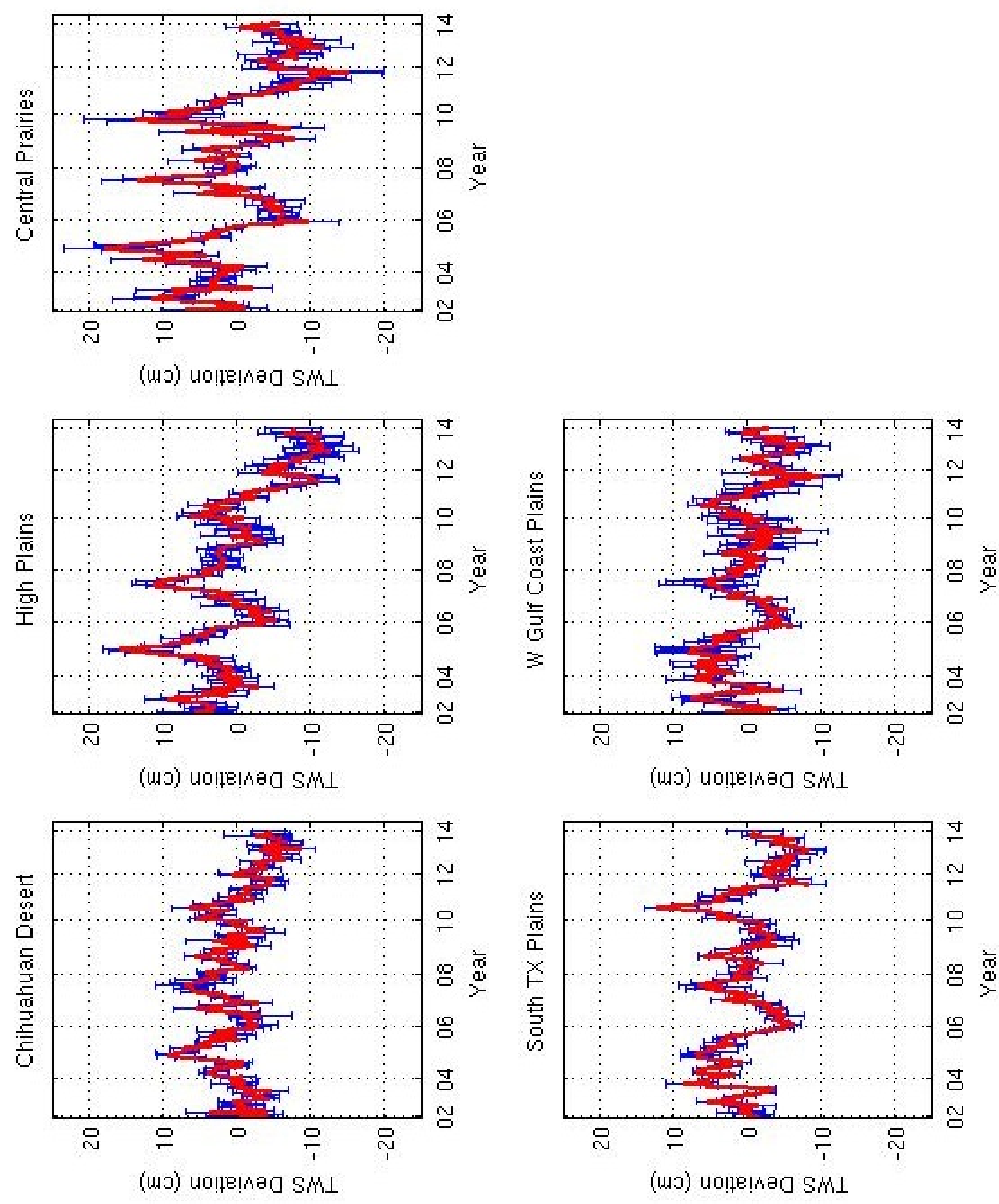

Figure 3.5: GRACE TWS Behavior (Final Organization)

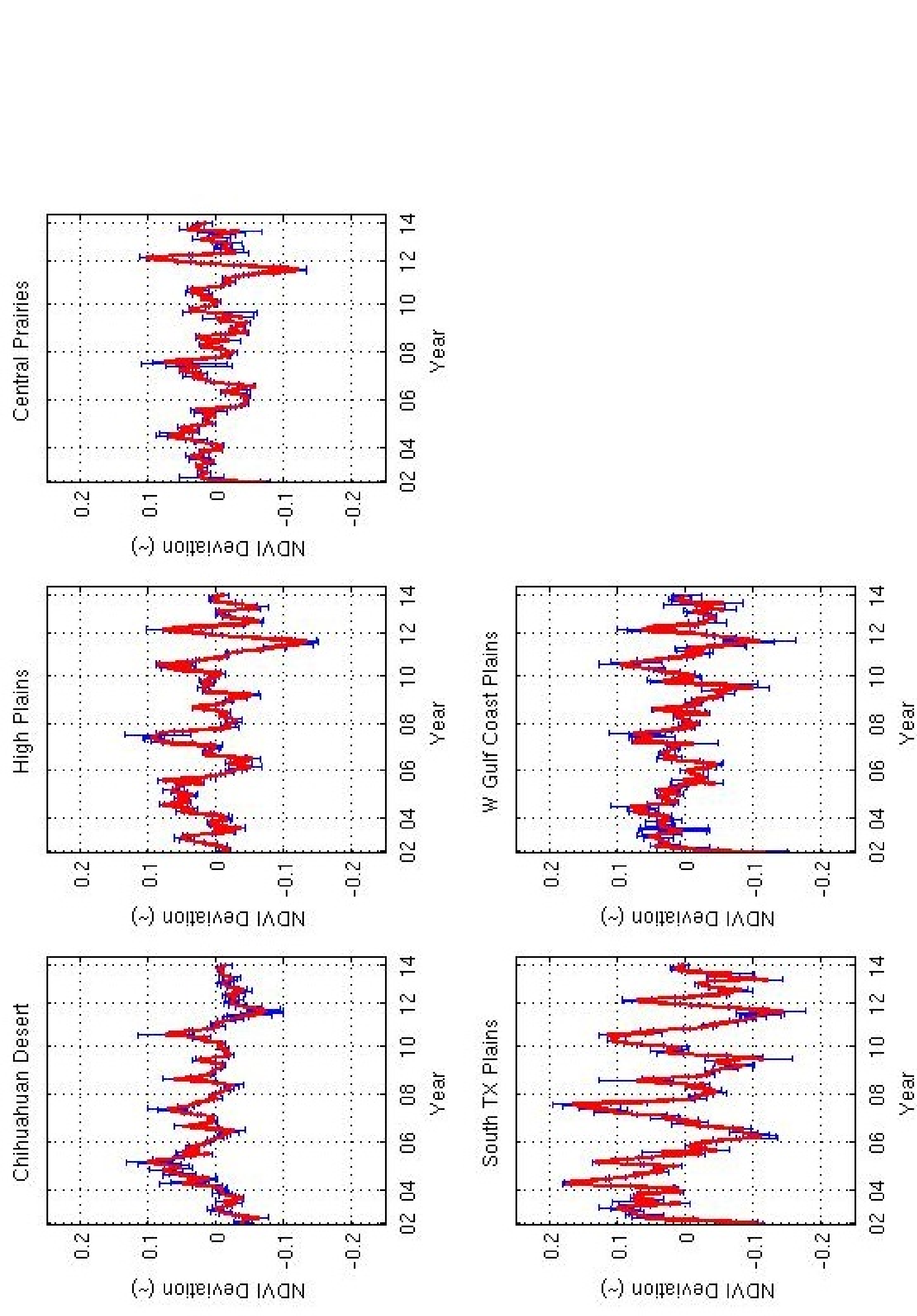

Figure 3.6: NDVI Behavior (Final Organization)

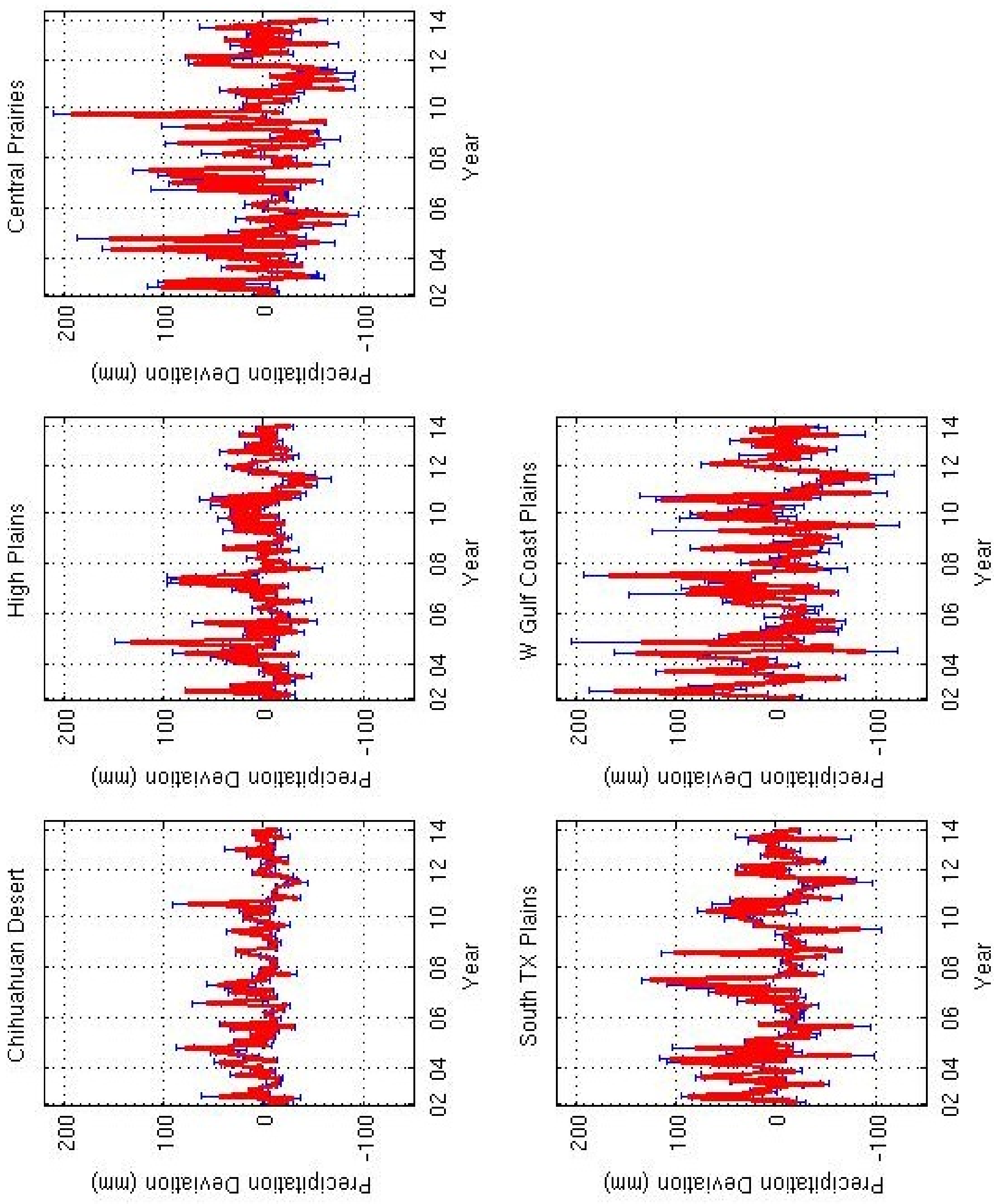

Figure 3.7: Precipitation Behavior (Final Organizaiton)

Chapter 4

Drought Index Background and Creation

Drought is the most severe natural hazard, affecting more people across the globe than any other natural phenomenon [6]. Despite this, characterizing drought and quantifying total water deficit remains a challenge [26]. Even defining drought remains difficult, as various authors tend to create new definitions over time to suit their needs [7]. Palmer (1965), Thornthwaite (1947), Thomas (1962), Tannehill (1947), and Friedman (1957) all define drought slightly differently, as authors continue to do today. Carr notes that there are some commonalities in most drought definitions, namely rainfall (the presence or lack thereof) and duration and magnitude of rainfall deficiency [7]. For this study, drought is defined as a prolonged period (3 or more months) with deficient water (as measured by rainfall, total water storage, and vegetation).

Creating one value to describe all the facets of a drought (its severity, duration, affected area etc.) is extremely challenging to do, as evidenced by the existence of multiple drought indices today. The drought index created in this study is not intended to consider all complexities associated with drought; rather, it is intended to show that GRACE TWS, NDVI, and precipitation data can meaningfully be fused together to identify periods of prolonged dryness.

4.1 Types of Drought

Prior to the early 1980s, there were over 150 definitions of drought being used [58]. Wilhite and Glantz surveyed existing literature at the time and developed four main categories of drought: meteorological, agricultural, hydrological, and socioeconomic. The schematic in Figure 4.1 is a good representation of how these droughts are related, and it also demonstrates the time lag among them [36].

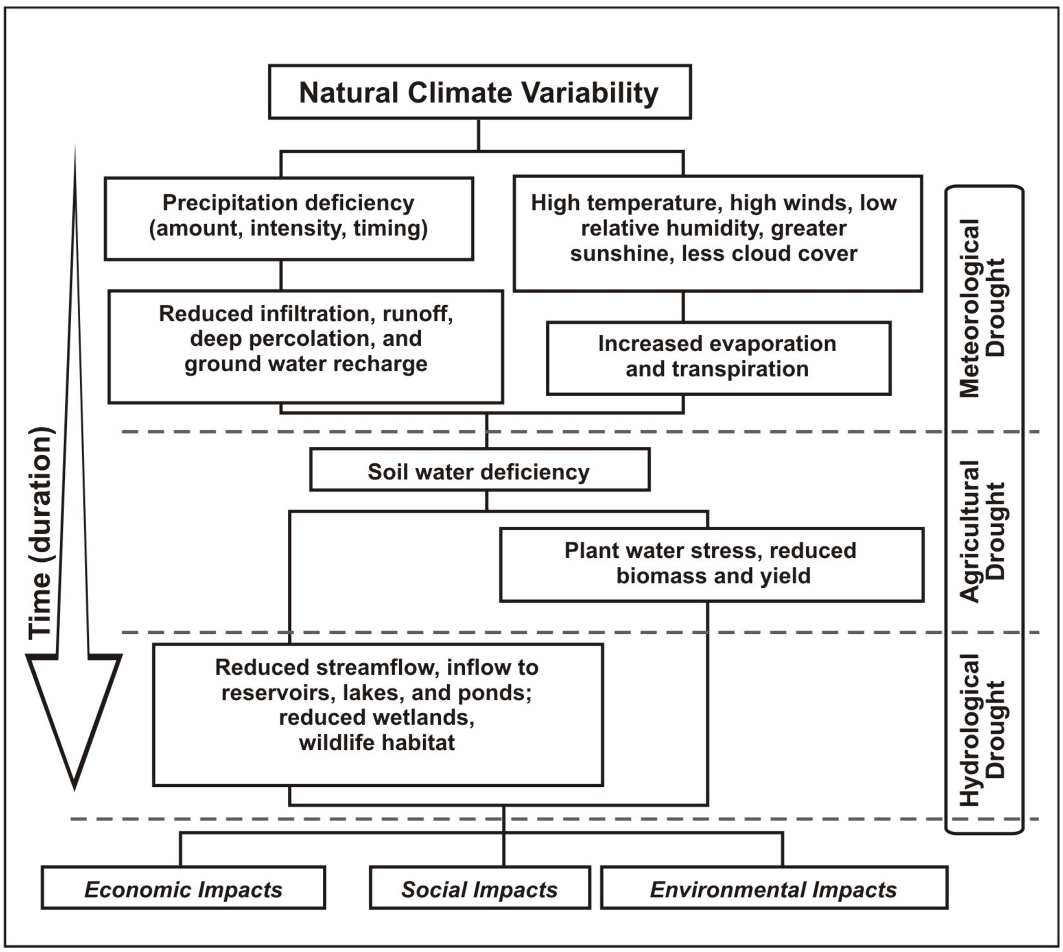

Figure 4.1: Drought Progession [36]

Meteorological drought is defined as a prolonged period with precipitation below normal [36]. Meteorological droughts are region specific because they are heavily influenced by atmospheric conditions, which vary from region to region. Drought indices such as the Palmer Drought Severity Index (PDSI), the Standard Precipitation Index (SPI), Percent Normal, and Vegetation Condition Index (VCI) are valuable in identifying meteorological drought.

Agricultural drought links characteristics of meteorological drought to agricultural impacts. It evaluates precipitation shortages, differences between actual and potential evapotranspiration soil water deficits, and reduced groundwater or reservoir levels [36]. It also accounts for seasonal variability in crops (i.e. growth, maturity, senescence).

Hydrological drought is characterized by a lack of water in subsurface hydrological systems (which could be due to effects of precipitation). It typically lags the development of meteorological and agricultural drought formation because it takes longer for water deficiencies to travel through the hydrological cycle to the subsurface systems. Indices such as the Palmer Hydrological Drought Index (PHDI), Surface Water Supply Index (SWSI), and Standardized Streamflow Index (SSFI) are useful for characterizing hydrological drought.

Socioeconomic drought is slightly different than the three types described above. It occurs when demand for a good exceeds the amount available as a result of weather-related water storage [36]. This drought is typically the last of the four to develop, and it is more difficult to characterize. It is not a focus of this study.

4.2 Overview of Existing Indices

Many indices have been developed to identify various types of drought, as well as for specific locations (i.e. regions with heavy snowpack vs. regions with no snowpack). The most common indices will be discussed here. The chosen indices are those for which data is readily available from NOAA's nClimDiv database, and data can be accessed at `ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv`.

4.2.1 Meteorological Drought Indices

The Palmer Drought Severity Index (PDSI) was developed by W. C. Palmer in 1965. It uses a soil moisture/water balance algorithm that is based on a series of daily air temperature and precipitation data [38]. The algorithm considers water supply (precipitation), demand (evapotranspiration), and loss (runoff). It was initially designed for data collected in the Great Plains (notably Kansas), and for that reason some argue it is an arbitrary index [2]. PDSI has several limitations including its PET estimation method, soil model, and runoff assumptions [40]. It uses a regional correction factor that was originally only based on data from nine locations. Additionally, the drought classification Palmer proposed was arbitrarily determined [40]. Despite these drawbacks, it is the most common drought index used in the US, perhaps in part due to the fact that it was the first drought index created for the US and has a long data record.

One of the other problems with PDSI was its tendency to rapidly change between positive and negative values. The Modified Palmer Drought Index (PMDI) was created to address this issue. PMDI has values equivalent to PDSI during an established wet or dry period, but PMDI differs during transition periods. In calculating PMDI, dry and wet probabilities are calculated, and their sum is used to avoid the drought index flipping between positive and negative values. It is continuous and more likely to be normally distributed than the PDSI [18]. Limitations on the PMDI are similar to those for the PDSI.

The Z-index (Moisture Anomaly Index) is calculated in a similar fashion to the PDSI (using the water balance algorithm). The Z-index is a measure of the departure of moisture conditions from normal. This index, then, is able to measure a month of above-normal precipitation even during periods of drought. Details on its calculation may be found in Quiring et al. [40]. Limitations for the Z-index are similar to those for the PDSI. The Z-index is similar to the precipitation deviation dataset used in this study, and it is expected they will have strong correlations.

The Standard Precipitation Index (SPI) was developed by McKee et al. in 1993 to better characterize moisture supply. It is based on statistical probability and is designed to be spatially invariant [31]. A long term precipitation record is required for the region of interest, and the SPI is then calculated by standardizing the probability of observed precipitation for any duration (one month to two years). Data available from the nClimDiv database provides SPI indices at one month, two month, three month, six month, nine month, one year and two year timespans. This flexibility allows SPI to be used to identify meteorological drought (short term one to three month spans) as well as hydrological drought (long term nine month to two year spans). Like the PDSI, the SPI has some limitations. Regions that regularly receive little to no precipitation are harder to evaluate with the SPI [60], and the index is heavily influenced by record length [59] and normalization procedure [40]. Table 4.1 summarizes the meteorological drought indices.

Index	Range	Characteristics
PDSI	-4 to +4	Calculated using water balance algorithm dependent upon temperature and precipitation
PMDI	-4 to +4	Calculated using water balance and modified during transitions between drought events
Z-index	-4 to +4	Calculated using moisture anomaly measurements
SPI (ST)	-2 to +2	Calculated using precipitation probability

Table 4.1: Meteorological Drought Index Summary

4.2.2 Hydrological Drought Indices

The Palmer Hydrological Drought Index (PHDI) uses the same input data as the PDSI. It differs from the PDSI in that it does not consider the long term trend [23]. PHDI values are identical to PDSI during an established wet or dry period, but the values diverge during transition periods. PHDI also differs from PDSI in that PHDI defines the end of a drought as the disappearance of a water deficit, while PDSI defines the end of a drought as the time when moisture conditions continuously erase the water deficit [19]. A limitation in PHDI calculation is that it does not correlate well with streamflow data [40]. Additionally, a qualitative evaluation by Quiring et al.

in 2007 found that PHDI is not well suited to quantify hydrological drought in Texas. Quiring's qualitative evaluation, however, is not sufficient to strike the use of PHDI from this study. Long-term SPI indices range from nine months to two years. SPI indices operating on these time spans are suitable for hydrological drought monitoring. Table 4.2 summarizes the hydrological drought indices.

Index	Range	Characteristics
PHDI	-4 to +4	Calculated using water balance algorithm dependent upon temperature and precipitation
SPI (LT)	-2 to +2	Calculated using precipitation probability for long timespans (9+ months)

Table 4.2: Hydrological Drought Index Summary

4.2.3 Dataset Drought Index Correlations

Each dataset is compared to existing drought indices to determine what type of drought each dataset best represents. The correlations are presented in Table 4.3 through Table 4.13. GRACE TWS best represents hydrological drought, NDVI best represents agricultural drought, and precipitation best represents meteorological drought.

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.74	0.88	0.56
HP	0.85	0.80	0.51
CP	0.83	0.66	0.47
STP	0.73	0.85	0.57
WGC	0.76	0.76	0.57

Table 4.3: Dataset - PDSI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.74	0.88	0.45
HP	0.85	0.72	0.34
CP	0.84	0.61	0.30
STP	0.79	0.79	0.41
WGC	0.82	0.71	0.38

Table 4.4: Dataset - PHDI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.44	0.57	0.92
HP	0.48	0.63	0.90
CP	0.50	0.55	0.87
STP	0.37	0.68	0.83
WGC	0.43	0.55	0.86

Table 4.5: Dataset - Z-index Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.75	0.90	0.55
HP	0.85	0.79	0.44
CP	0.85	0.67	0.39
STP	0.77	0.85	0.49
WGC	0.80	0.76	0.47

Table 4.6: Dataset - PMDI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.35	0.45	0.85
HP	0.29	0.44	0.89
CP	0.33	0.43	0.88
STP	0.22	0.52	0.82
WGC	0.32	0.42	0.85

Table 4.7: Dataset - 1-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.48	0.60	0.66
HP	0.46	0.65	0.66
CP	0.53	0.64	0.67
STP	0.38	0.74	0.67
WGC	0.48	0.66	0.68

Table 4.8: Dataset - 2-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.54	0.66	0.58
HP	0.58	0.75	0.63
CP	0.63	0.73	0.59
STP	0.46	0.80	0.62
WGC	0.57	0.72	0.62

Table 4.9: Dataset - 3-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.57	0.77	0.50
HP	0.70	0.84	0.51
CP	0.71	0.70	0.44
STP	0.63	0.80	0.51
WGC	0.70	0.72	0.45

Table 4.10: Dataset - 6-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.61	0.80	0.43
HP	0.75	0.73	0.37
CP	0.78	0.62	0.34
STP	0.72	0.72	0.40
WGC	0.78	0.70	0.39

Table 4.11: Dataset - 9-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.62	0.79	0.36
HP	0.77	0.63	0.29
CP	0.79	0.57	0.25
STP	0.72	0.67	0.31
WGC	0.78	0.64	0.32

Table 4.12: Dataset - 12-Month SPI Correlation Coefficients

Ecoregion	GRACE TWS	NDVI	Precipitation
CD	0.63	0.70	0.22
HP	0.73	0.37	0.12
CP	0.66	0.25	0.08
STP	0.66	0.51	0.16
WGC	0.69	0.46	0.18

Table 4.13: Dataset - 24-Month SPI Correlation Coefficients

PDSI correlates most strongly with GRACE TWS (High Plains, Central Prairies) or NDVI (Chihuahuan Desert, South TX Plains, West Gulf Coast Plains) depending on the region. PDSI is a long-term meteorological index, so the high correlation with both NDVI and GRACE TWS was not surprising. In this context, long-term refers to a time frame on the order of six months. This multi-month duration reflects a duration long enough to discern changes in NDVI and GRACE TWS.

PHDI correlates most strongly with GRACE TWS in every region except the Chihuahuan Desert, where it correlates with NDVI. This is expected because GRACE TWS is a long-term water storage measurement. The exception of the arid desert is interesting. It is possible that the GRACE TWS signal there is too small to form meaningful correlations (the signal may actually have low amplitude, or the signal retained after the de-striping and smoothing processes is small). The NDVI deviations in the Chihuahuan Desert are smaller than other regions in Texas, but they are significant enough to correlate with PHDI.

The Z-index correlates most strongly with precipitation in every region, which is to be expected. It has a higher degree of correlation (0.91 compared to 0.83) in more arid areas (Chihuahuan Desert, High Plains). In these more arid areas, the deviations are more significant, potentially accounting for the higher correlation.

PMDI correlates most strongly with GRACE TWS (High Plains, Central Prairies, West Gulf Coast Plains) and NDVI (Chihuahuan Desert, South TX Plains). This index is similar to PDSI, so the lack of correlation with precipitation is not unusual.

Correlations with the SPI vary according to timespan. 1-Month SPI has the strongest correlation with precipitation in every region. Both are short-term phenomena, which explains this behavior. 2-Month SPI has the strongest correlation with precipitation (Chihuahuan Desert, Central Prairies, and West Gulf Coast Plain) and NDVI (High Plains, South Texas Plains). As NDVI and precipitation are both short-term phenomena (relative to GRACE TWS), agreement with 2-Month SPI is not surprising. Disparate ecoregion types (i.e. the desert and east Texas) both exhibit strong correlations between 2-Month SPI and precipitation. This suggests that 2-Month SPI behaves the same way regardless of geography. 3-Month SPI has the strongest correlation with NDVI in every region. Three months can be treated as a transition from meteorological to agricultural drought. The high correlation with NDVI suggests NDVI is an appropriate dataset to monitor agricultural drought.

6-Month SPI has the strongest correlation with NDVI in every region. The correlations are slightly larger (not significantly so) than those for the 3 month span, corroborating the assertion that NDVI is capable of identifying agricultural drought. 9-Month SPI has the strongest correlation with NDVI (Chihuahuan Desert, High Plains, South TX Plains) and GRACE TWS (Central Prairies, West Gulf Coast Plain). The correlation with GRACE TWS suggests that the 9-Month SPI index is more indicative of a hydrological drought, and the fact that both regions are wet areas suggest that their GRACE TWS signal is large enough to develop this correlation. The correlation with NDVI in the more arid areas of the state suggests that the GRACE TWS signal is not large enough to correlate with 9-Month SPI. 12-Month SPI has the strongest correlation with GRACE TWS in every region except the Chihuahuan Desert, where it correlates with NDVI. This time span is a hydrological drought, which explains the high correlation with GRACE TWS. Again, the fact that the most arid part of the state has a higher correlation with a vegetation index could be an artifact of the low-amplitude GRACE TWS signal in this region. However, this arid landscape also has sparse vegetation, so this correlation with NDVI may be less significant. 24-Month SPI has the strongest correlation with GRACE TWS in every region except the Chihuahuan Desert. Two years' duration marks a hydrological drought, explaining the agreement with GRACE TWS. The high correlation with NDVI may be insignificant due to the small vegetation signal in the region.

4.3 Merged-dataset Drought Index

The spatial and temporal complexity of drought make it difficult to devise a universal drought index [32]. The index created in this study is designed for Texas. Because of the datasets used, it is not intended to be a universal index. For similar ecological and climate regimes, however, this index may still have similar performance.

4.3.1 MDI Calculation

The datasets chosen for this study have different spatial and temporal resolutions that must be reconciled before an index is calculated. Uniform spatial resolution is achieved by considering spatial averages across the defined sub-regions of Texas. Uniform temporal resolution is achieved by creating a monthly timeseries for each dataset.

Annual signals in the datasets are also considered. A monthly climatology (based on April 2002 - January 2014 data) is calculated for each dataset. For each dataset, each month is differenced from the climatology, and the resulting deviation values are incorporated into MDI. Removing the annual signal in all sub-regions of Texas mitigates spatial variance. Deviation z-scores (equation 4.1) are calculated for direct comparison among the datasets. This standardization method has been used in previous drought index calculation studies [32, 39].

$$Z_{TWS} = \frac{TWS(k) - \overline{TWS}}{\sigma_{TWS}} \tag{4.1}$$

The Merged-dataset Drought Index (MDI) is defined as:

$$Z_C = Z_{TWS} + Z_{NDVI} + Z_{Precipitation} \tag{4.2}$$

$$MDI = \frac{Z_C(k) - \overline{Z_C}}{\sigma_{Z_C}} \tag{4.3}$$

MDI is normalized about zero, and positive values represent a surplus, while negative values represent a deficiency. Droughts are defined as a period of prolonged dryness, and this study requires a three month minimum to categorize the deficits as a drought event.

To evaluate the total severity of a drought event, the affected land area is also considered. Total severity is calculated only after a drought event has been identified, and this study calculates severity once a drought has ended. It may be calculated on a rolling time scale, however, if a region is currently in drought. Some regions of Texas, for example, are currently in drought, so total severity calculations reflect the severity to that point in time. Total severity (TS) is calculated according to equation 4.4. Numerical integration is used to approximate the cumulative MDI over the drought duration, and the affected area is considered via weight factors. These factors, given in Table 4.14, represent each region's percent area of the state.

$$TS = \int_{t_1}^{t_2} MDI\, dt * Area\, Weight\, Factor \tag{4.4}$$

Region	Area (km^2)	Weight Factor (%)
Chihuahuan Desert	91,000	13
High Plains	311,000	46
Central Prairies	160,000	24
South Texas Plains	54,000	8
West Gulf Coast Plain	61,000	9
Total	677,000	100

Table 4.14: Region Weight Factors

Using the MDI values for the past 12 years, a classification system is designed to quantitatively categorize drought severity on a monthly basis. This classification system is applied monthly and discussed in Chapter 4.3.4. A separate classification scheme based on drought event total severity is discussed in Chapter 4.4.

4.3.2 Correlation with Drought Indices

The MDI is compared to existing indices using the Pearson correlation coefficient to evaluate index similarity and event identification capabilities. Existing drought index data (PDSI, PHDI etc.) is available through NOAA and is organized at the state and climate division level. The state of Texas comprises 10 climate divisions. Climate division refers to an organization scheme used by the National Climatic Data Center of NOAA, which is influenced by county (political) boundaries. These divisions are slightly different than the Level III ecoregions, but can be aggregated to match the final organization scheme in Figure 3.4. A map showing the differences between the two organization schemes is shown in Figure 4.2. The original climate division outlines are in pink, and the climate divisions aggregated to match the "super-regions" are in dark red. Level III ecoregions are outlined in gray, and the aggregated "super-regions" are outlined in dark gray. The correlation study is performed after the climate divisions are aggregated to match the existing organization scheme.

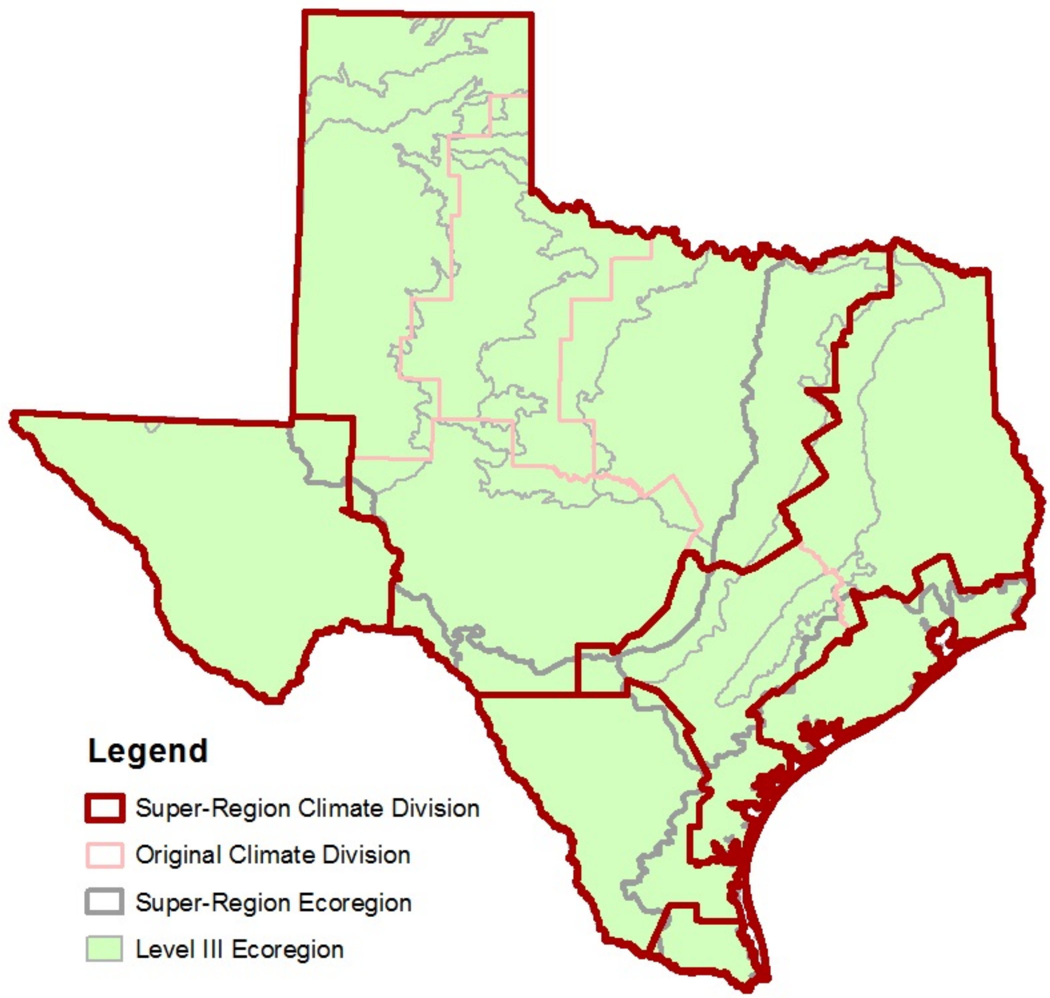

Figure 4.2: Region Division Comparison

Table 4.15 displays the results of the correlation study by region.

Index	CD	HP	CP	STP	WGC	Average
PDSI	0.87	0.89	0.84	0.89	0.86	0.87
PHDI	0.83	0.79	0.74	0.82	0.78	0.79
Z-index	0.77	0.83	0.81	0.78	0.75	0.79
PMDI	0.88	0.86	0.81	0.87	0.84	0.85
SPI 1	0.66	0.67	0.70	0.64	0.65	0.67
SPI 2	0.70	0.73	0.78	0.74	0.74	0.74
SPI 3	0.71	0.81	0.83	0.78	0.78	0.78
SPI 6	0.74	0.84	0.78	0.80	0.77	0.79
SPI 9	0.74	0.76	0.73	0.76	0.77	0.75
SPI 12	0.71	0.69	0.68	0.71	0.72	0.70
SPI 24	0.62	0.50	0.42	0.55	0.55	0.53

Table 4.15: Merged-dataset Drought Index Correlation Study

MDI correlated most strongly with PDSI, PMDI, PHDI, Z-index, SPI 6, SPI 3, and SPI 9. The extreme SPI indices (SPI 1, SPI 2, SPI 12, and SPI 24) had relatively poorer correlations.

This strong correlation with nearly every current drought index proves that MDI is a viable measurement of drought events in Texas. Furthermore, this index correlates well with both meteorological and hydrological drought indicators, showing it is capable of identifying different kinds of drought.

4.3.3 Other Experimental Indices

In addition to MDI, three experimental indices were created and evaluated. These indices used dataset pairs. Water Vegetation Index (WVI) is based on GRACE TWS and NDVI, Total Water Index (TWI) is based on GRACE TWS and precipitation, and Precipitation Vegetation Index (PVI) is based on precipitation and NDVI. The correlations of these indices with existing drought indices are shown in Table 4.16, Table 4.17, and Table 4.18.

Index	CD	HP	CP	STP	WGC
PDSI	0.87	0.90	0.85	0.88	0.84
PHDI	0.87	0.86	0.82	0.87	0.85
Z-index	0.54	0.61	0.60	0.58	0.54
PMDI	0.88	0.90	0.86	0.90	0.87
SPI 1	0.43	0.40	0.43	0.41	0.41
SPI 2	0.58	0.61	0.66	0.62	0.63
SPI 3	0.65	0.73	0.77	0.70	0.71
SPI 6	0.72	0.85	0.79	0.79	0.79
SPI 9	0.76	0.81	0.79	0.80	0.82
SPI 12	0.76	0.77	0.77	0.77	0.79
SPI 24	0.72	0.60	0.52	0.65	0.64

Table 4.16: Water Vegetation Index Correlation Study

Index	CD	HP	CP	STP	WGC
PDSI	0.79	0.84	0.81	0.82	0.81
PHDI	0.72	0.73	0.70	0.76	0.73
Z-index	0.82	0.85	0.85	0.76	0.78
PMDI	0.78	0.79	0.76	0.80	0.78
SPI 1	0.73	0.73	0.75	0.66	0.71
SPI 2	0.69	0.69	0.74	0.66	0.70
SPI 3	0.68	0.74	0.75	0.69	0.72
SPI 6	0.64	0.75	0.71	0.72	0.70
SPI 9	0.63	0.69	0.69	0.71	0.71
SPI 12	0.60	0.65	0.64	0.66	0.67
SPI 24	0.51	0.52	0.46	0.52	0.53

Table 4.17: Total Water Index Correlation Study

Index	CD	HP	CP	STP	WGC
PDSI	0.83	0.76	0.68	0.80	0.77
PHDI	0.76	0.62	0.54	0.68	0.63
Z-index	0.86	0.89	0.85	0.85	0.81
PMDI	0.83	0.72	0.63	0.76	0.71
SPI 1	0.75	0.78	0.78	0.76	0.74
SPI 2	0.72	0.77	0.78	0.80	0.77
SPI 3	0.71	0.81	0.79	0.80	0.78
SPI 6	0.73	0.79	0.67	0.74	0.68
SPI 9	0.70	0.64	0.57	0.64	0.63
SPI 12	0.66	0.53	0.49	0.56	0.56
SPI 24	0.53	0.28	0.20	0.38	0.37

Table 4.18: Precipitation Vegetation Index Correlation Study

This study shows that the Precipitation Vegetation Index has superior performance to MDI for short-term meteorological drought identification, evidenced by the high correlations with the Z-index, SPI 1, SPI 2, and SPI 3. Considering all drought types, MDI is a better index than WVI, TWI, or PVI because MDI presents a more robust picture of the current drought conditions. Each index (MDI, WVI, TWI, PVI) was calculated by equally weighting each input dataset. Current experimental drought index blends typically use a weighting scheme [40], and a weighted MDI is discussed in Chapter 5.1.2.

4.3.4 Drought Classification Scheme

MDI is calculated every month across all sub-regions beginning in April 2002. To compare MDI values spatially and temporally, a classification scheme is developed. The classes follow those currently used by the US Drought Monitor. This integrates interpretation of MDI into the current framework used for drought identification.

The classification strategy was developed using monthly MDI values during identified droughts (discussed in Chapter 4.4). An iterative process utilized a series of histograms to find natural groupings in the data. Initial organizations employed too many classes to be consistent with the current classification methodologies, so the final histogram was designed with six bins. The classification scheme also considered the "energy" needed to move up a class. During drought onset, minor deficits can cause significant changes. As droughts progress, the strain the environment is already under can cause large deficits to induce minor changes. Accordingly, less severe drought events are more common.

The final histogram is shown in Figure 4.3. The colors used in the histogram denote the drought severity and match those used in the monthly MDI maps (for example, Figure 4.4). As seen in the figure, the natural groupings occur irregularly, so the bin sizes were slightly adjusted to represent a more standard size. The final scheme is provided in Table 4.19.

MDI Value	Classification	Description
0 to -0.45	Unclassified	Normal
-0.45 to -0.90	D0	Abnormally Dry
-0.90 to -1.35	D1	Moderate Drought
-1.35 to -1.80	D2	Severe Drought
-1.80 to -2.20	D3	Extreme Drought
-2.20 and less	D4	Exceptional Drought

Table 4.19: MDI Classification Scheme

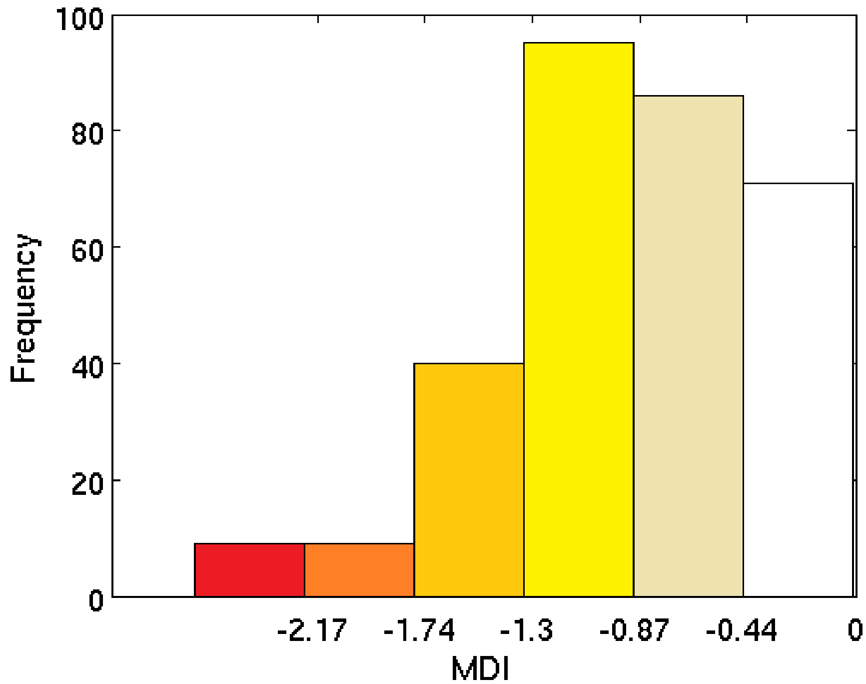

Figure 4.3: MDI Histogram

Some examples of monthly MDI maps are presented in Figure 4.4 through Figure 4.6. MDI does not directly depend on the previous month's data, so these maps are best viewed sequentially. For brevity, selected months are shown. One of the most severe droughts identified occurred in 2011. Figure 4.4 shows the entire state is already in moderate to severe drought in May 2011, and at the drought's peak in September, Figure 4.5 shows that 79% of the state is in exceptional drought. A year later in September 2012, Figure 4.6 shows that the region has recovered, with only 30% of the state in moderate drought.

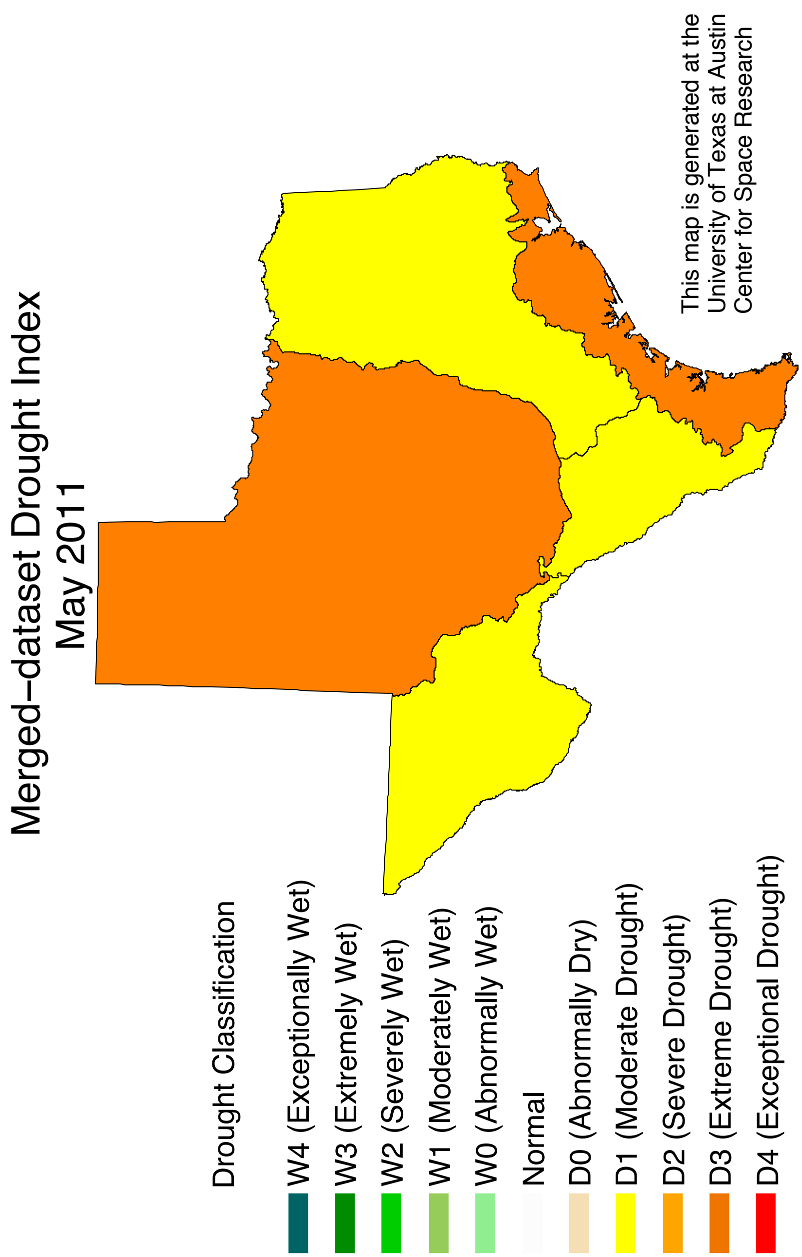

Figure 4.4: MDI May 2011

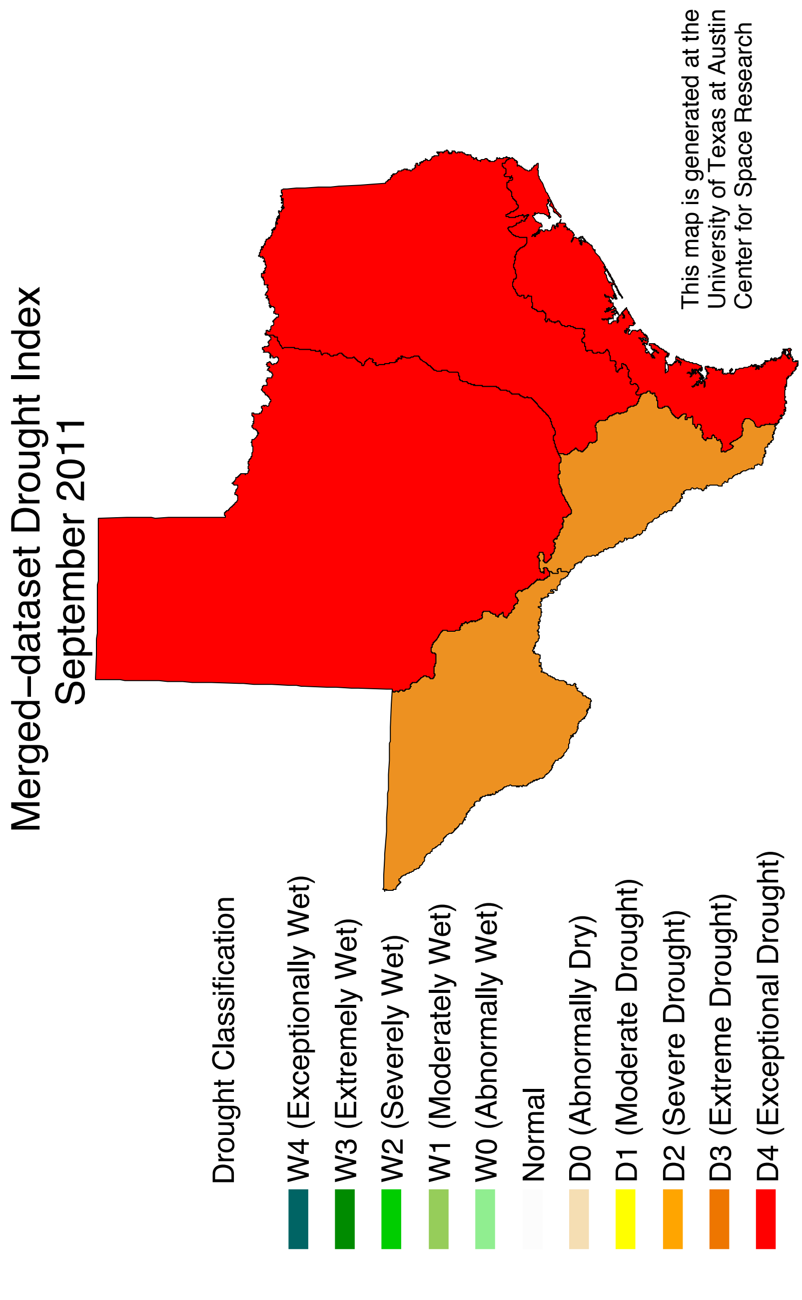

Figure 4.5: MDI September 2011

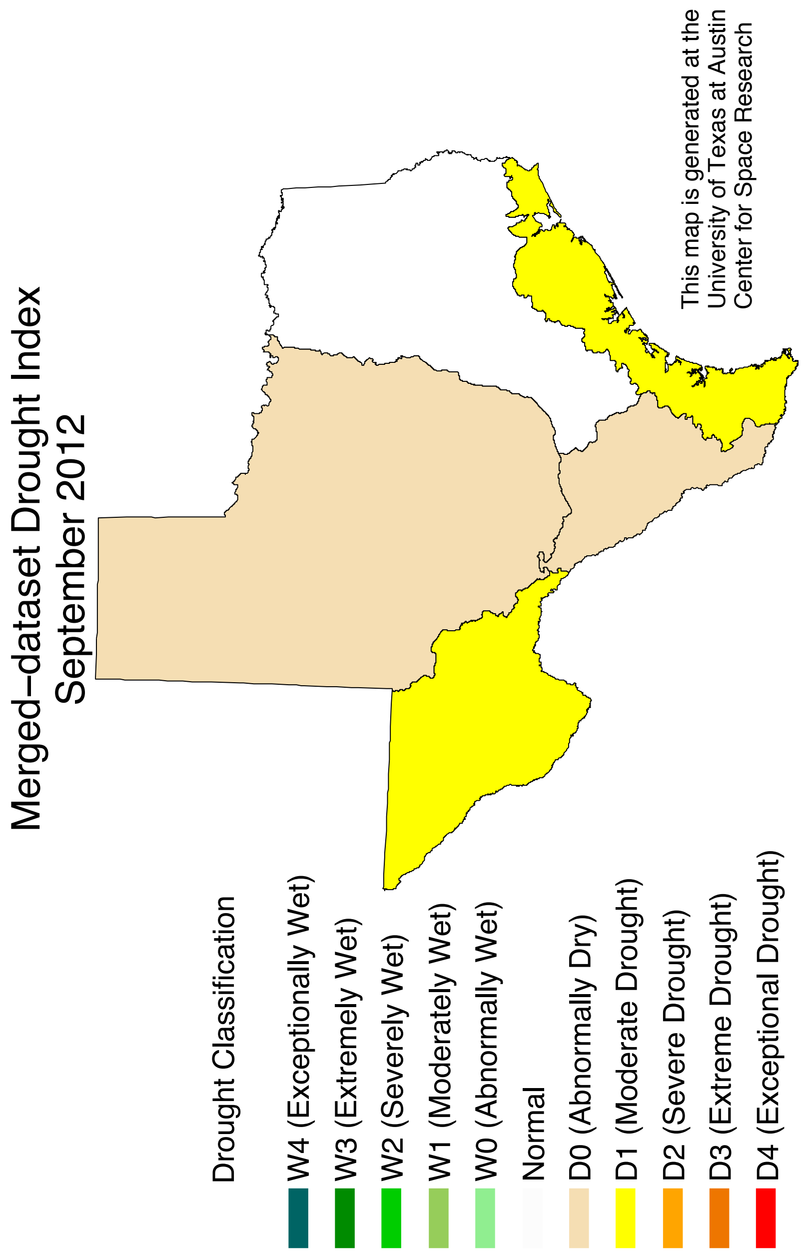

Figure 4.6: MDI September 2012

4.4 Drought Event Identification and Classification

MDI behavior is presented in Figure 4.7. Orange shading denotes an identified drought event. A qualitative analysis of the trends show some similarities and differences across the state. The peak deficit for any drought occurs in late 2011 for every region, but that deficit magnitude varies across the state. It is more severe in eastern Texas (Central Prairies, West Gulf Coast Plains) where the negative departure is more significant relative to the normal. MDI identifies five droughts in every region except the Chihuahuan Desert, where it identifies six. The Chihuahuan Desert experienced a drought in the late spring through early fall of 2002, where the rest of the state did not. This is the only drought event identified in this study that only occurs in one region. All remaining drought events that were identified occurred in at least two regions, though the times they occurred may not exactly overlap. The identified droughts and their characteristics are presented in Table 4.20 through Table 4.24. Cumulative MDI refers to the sum of the MDI values over the drought duration, and it is a unitless quantity. 'TS' refers to total severity, which is defined by equation 4.4 (Chapter 4.3.1), and has units of months. The Total Severity Classification is described below.

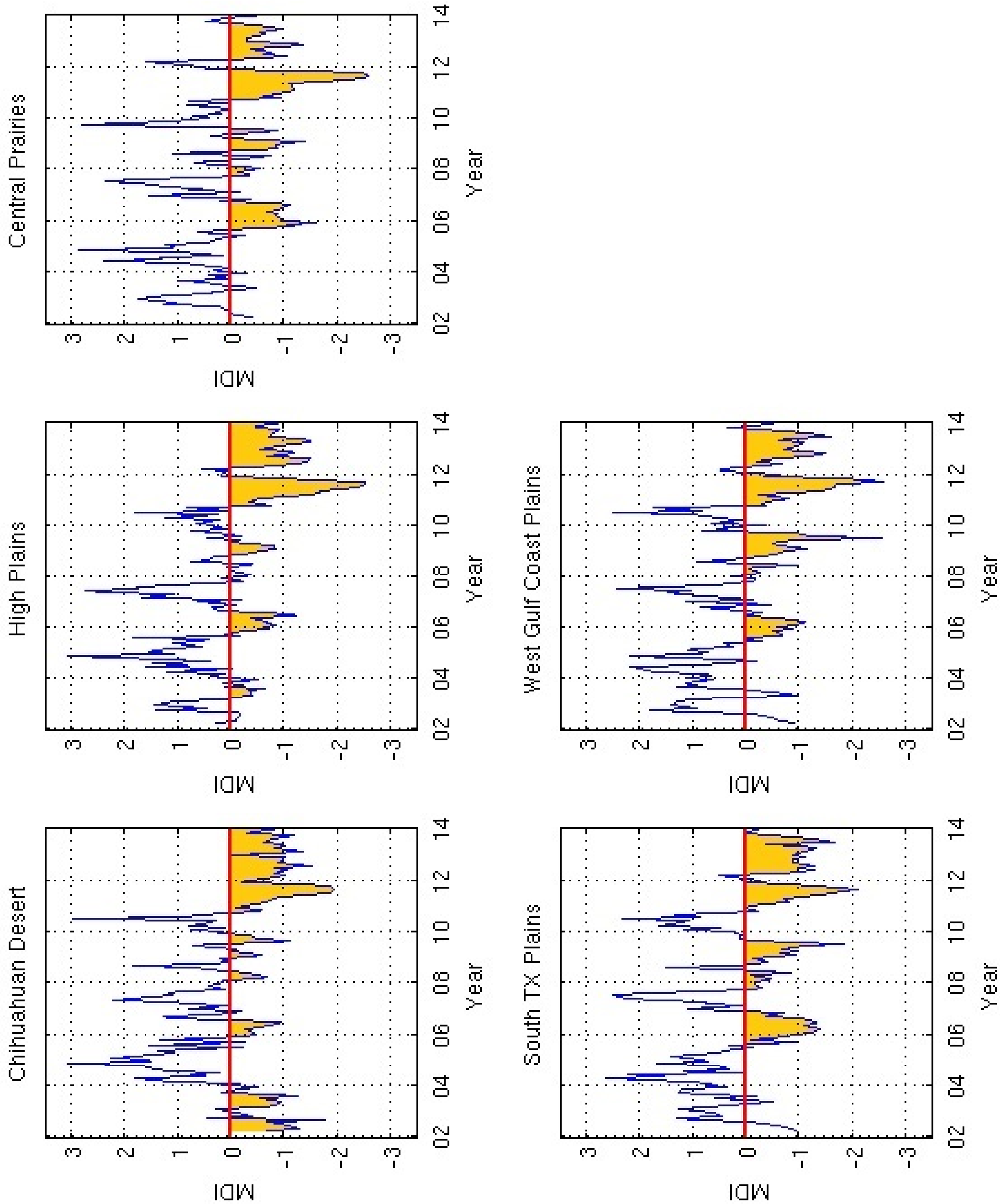

Figure 4.7: MDI Behavior Across Regions

Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
April 2002	October 2002	7	-5.9	-0.79	Unclassified
March 2003	September 2003	7	-5.0	-0.68	Unclassified
December 2005	July 2006	8	-3.9	-0.52	Unclassified
March 2008	June 2008	4	-1.6	-0.21	Unclassified
January 2009	November 2009	11	-2.7	-0.36	Unclassified
October 2010	January 2014	40	-35.6	-4.79	TS2

Table 4.20: Chihuahauan Desert Drought Events

Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
April 2003	August 2003	5	-1.4	-0.66	Unclassified
November 2005	August 2006	10	-6.7	-3.08	TS1
September 2008	June 2009	8	-3.2	-1.45	TS0
October 2010	November 2011	14	-18.5	-8.49	TS4
April 2012	January 2014	22	-21.0	-9.64	TS4

Table 4.21: High Plains Drought Events

Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
September 2005	September 2006	13	-11.8	-2.8	TS1
October 2007	February 2008	5	-1.3	-0.31	Unclassified
October 2008	August 2009	11	-6.1	-1.44	TS0
October 2010	November 2011	14	-19.8	-4.69	TS2
April 2012	September 2013	18	-11.2	-2.66	TS1

Table 4.22: Central Prairies Drought Events

Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
September 2005	November 2006	15	-12.5	-1.0	TS0
October 2007	June 2008	9	-2.4	-0.19	Unclassified
October 2008	September 2009	12	-8.3	-0.67	Unclassified
October 2010	February 2012	17	-12.5	-1.0	TS0
April 2012	January 2014	22	-19.1	-1.5	TS0

Table 4.23: South Texas Plains Drought Events

Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
June 2005	June 2006	13	-7.2	-0.65	Unclassified
February 2008	July 2008	6	-1.6	-0.14	Unclassified
October 2008	September 2009	12	-10.2	-0.92	TS0
October 2010	January 2012	16	-17.1	-1.53	TS0
April 2012	October 2013	19	-15.6	-1.40	TS0

Table 4.24: West Gulf Coast Plain Drought Events

Based on these identified drought events, a classification scheme was devised to judge the total severity of one drought event relative to another. The scheme uses categories based on the US Drought Monitor. Multiple strategies were considered, and the first was based on the cumulative MDI. In this method, however, small areas in severe drought were equivalent to large areas in mild drought, so further distinction was necessary. For this reason, Total Severity, which incorporates region area, (equation 4.4) was used to classify drought events. Considering affected area is important for socioeconomic droughts because it incorporates how many individuals will be affected. Population density also plays a role. As an example, consider an event in the Chihuahuan Desert (weight factor = 0.13) with a cumulative MDI of 35 and Total Severity of 4.8 and a second event in the High Plains (weight factor = 0.45) with a cumulative MDI of 21 and a Total Severity of 9.6. Based solely on the MDI values, the event in the desert is 60% worse than that in the High Plains. Based on total severity, however, the event in the High Plains is twice as bad.

The total severity "bin size" was based on a histogram of total severity values for all identified droughts, shown in Figure 4.8. Color denotes the TS Class, and the most populated bin was divided into two classes. Additionally, each class size considered the amount of "energy" needed to move up a class. During drought onset, small deficits result in significant changes. As droughts progress, the strain the environment is already under causes large deficits to result in minor changes. It does not take a large deficit to push an event from being near normal to a TS0 (abnormally dry) event, but it does require larger deficiencies (more energy) to become a TS1 (moderate drought) event. Even more energy is required to become a TS2 (severe drought). At this level, the environment is in a highly stressed state, so the amount of energy needed to reach TS3 (exceptional) and TS4 (extreme) is the same. This is reflected in the strategy shown in Table 4.25. As seen, not all severity classes contain an identified event. This was a conscious choice in designing the scheme. Natural groupings of total severity values exist, but there are also significant gaps. With only 12 years of data, this is the best available scheme, but it it will become more complete with a longer data record.

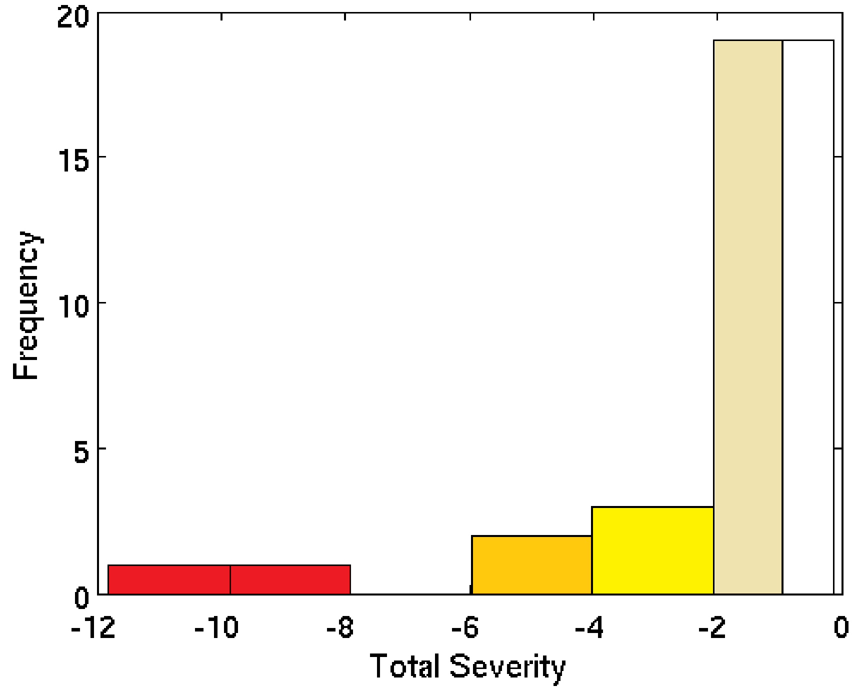

Figure 4.8: Total Severity Histogram

Total Severity Value	Total Severity (TS) Classification	Characteristics	No. Identified Events
0 to -0.8	Unclassified	Normal	11
-0.8 to -2	TS0	Abnormally Dry	8
-2 to -4	TS1	Moderate Drought	3
-4 to -6	TS2	Severe Drought	2
-6 to -8	TS3	Extreme Drought	0
-8 and less	TS4	Exceptional Drought	2

Table 4.25: Total Severity Classification Scheme

This classification scheme is applicable to multi-month events and is developed based on the identified droughts in Texas. The TS classification scheme and drought severity scheme are designed specifically for Texas, and modifications may be required for outside applications. Calculation of MDI itself is independent of geography, and it can be calculated for any region with available data.

With this scheme in mind, the drought events are discussed. Colors are used to denote events that occur in similar time frames in different regions. The first event seen across the whole state occurred from late 2005 to mid-2006. In the non-arid parts of the state, the drought began in August - October 2005 and ended June - November 2006. This drought manifested itself differently across the state. It was mild in the arid Chihuahuan Desert, and the total severity does not identify it as a drought, while it was class TS1 in the Central Prairies. This event had different durations and peak deficits in the sub-regions.

The next event seen across the state occurred from late 2008 to late 2009. This event again manifested itself differently across the state, being more severe in wetter parts of the state (Central Prairies and West Gulf Coast Plain). The final event (in the time period studied) occurring across the state began in October 2010. The Chihuahuan Desert was in a constant state of drought until the end of the study period, January 2014. The remaining four regions identify two separate events during this time. The High Plains and the Central Prairies experienced a four month reprieve (December 2011 through March 2012), the South Texas Plains a one month reprieve (March 2012), and the

West Gulf Coast Plains experienced a two month reprieve (February to March 2012). This brief positive respite between drought events may be artificial in some regions because it is unlikely that the system completely recovers so quickly. It is more likely that a rapid increase in one signal (precipitation or vegetation) artificially inflated the index. A drought is identified after three months of deficiencies in MDI, so an end to drought is defined as at least three consecutive months of positive MDI values. This causes reclassification of four events, two in the South Texas Plains and two in the West Gulf Coast Plain. Each pair are consolidated into a single drought event. This change is reflected in Table 4.26.

Region	Begin Date	End Date	Duration (months)	Cumulative MDI	TS (months)	TS Class
STP	October 2010	January 2014	40	-31.4	-2.52	TS1
WGC	October 2010	October 2013	37	-32.0	-2.87	TS1

Table 4.26: Drought Reclassification

The West Gulf Coast Plains identify the ending date of its last drought as October 2013, while the Central Prairies identifies the ending date as September 2013. The Chihuahuan Desert, High Plains, and South Texas Plains remain in drought through January 2014. The regions with droughts ending prior to January 2014 experienced brief reprieves after their respective droughts ended, but as of January 2014, every region in Texas is in some stage of drought. In every region, the events from October 2010 to January 2014 were more severe than other droughts (larger cumulative MDI and total severity values). Most of the events were classified as more severe (at least TS1), and the only occurrence of TS4 events during the time period studied (2002 - 2014) occurred during October 2010 to January 2014 in the High Plains.

Cumulative dataset deficits during drought events are also considered. For the identified droughts, all signals exhibited a deficiency except in two instances. The first instance occurred April to August 2003 in the High Plains, and GRACE TWS experienced a net gain of 5.1 km^3. This is the only event identified in the High Plains that was classified as no drought, and this GRACE TWS finding supports that designation. The second instance occurred in the South Texas Plains from October 2007 to June 2008, and GRACE TWS had a net gain of 3.8 km^3. Again, this event was classified as no drought, so the GRACE TWS finding supports that.

For identified events consequently designated "No Drought" ("Unclassified") by the total severity classification system, deficiencies in each dataset can serve as a warning. The deficiencies may not be significant enough to indicate drought, but the regions in questions should be closely monitored. The total severity calculations can be calculated on a rolling basis to determine what areas are at risk.

Chapter 5

Drought Analysis

Identified droughts are discussed in this chapter. MDI successfully identifies multiple droughts, and event characteristics vary by region. MDI has shown strong correlation to PDSI, and behavioral differences between indices are discussed. A significant adjustment to MDI is the development of a weighting scheme that balances inputs from hydrological and meteorological indicators, and the contribution of GRACE TWS is expanded.

5.1 Merged-dataset Drought Index

This section discusses multiple aspects of the developed index, including considerations in using MDI, signal weighting modifications, and index robustness.

5.1.1 Usage Considerations

Temporally, MDI is calculated for every month starting in April 2002 (first month of available GRACE TWS data). Throughout the GRACE mission, there are occasional GRACE TWS data gaps. Interpolation was used to fill these gaps, but the MDI values for these months are less stable. It could also be argued that the MDI is not valid at all for months where one of the datasets does not provide information. This index is based on 12 years of data, which is shorter than the 30 year period typically used to establish normal behavior. As more data becomes available, the index can continue to be refined and re-evaluated.

Previous drought indices based on vegetation measurements are only calculated for growing months (March through October, depending on location) or only considered during those months. MDI uses two other datasets, GRACE TWS and precipitation, that are not limited in this way, so MDI can be calculated and analyzed year-round. When analyzing events in winter months, however, the size of the NDVI signal should be considered. Typically, mild winters in Texas have a less significant impact on vegetation senescence than in northern latitudes, however.

This index was developed specifically for Texas geography. Previous studies have found that various regions have multiple water source types which require different formulations for drought monitoring. Colorado, for example, has a significant amount of snowpack that is not considered in PDSI calculations, so another index, the Surface Water Supply Index (SWSI) is used to complement the PDSI information. Other indices can be used to complement the MDI in Texas, and if MDI is desired outside of Texas, further work will be necessary to assess how ecological differences in new study areas impact the formulation of the MDI. One of those differences would likely be GRACE TWS signal amplitude (i.e. if there is a stronger GRACE TWS signal, weighting schemes may change, or other datasets may be used in the formulation).

The spatial resolution of MDI is limited by GRACE TWS, and improvements in resolution will refine MDI formulation. Both NDVI and precipitation data are available at finer resolutions and are currently utilized in drought indices that operate at the county level. The MDI cannot operate on those scales, which is a disadvantage of this index. To make MDI operational at the climate division level, gravity signal resolution would need to improve by at least 50% to 250 km, and to operate at the county level, the resolution would need to improve an order of magnitude to 50 km. These values are a baseline for the necessary spatial resolution required from future geodetic space missions for use in drought identification at smaller scales.

5.1.2 Signal Weighting

Consideration of vegetation senescence's impact on MDI led to developing a signal weighting scheme. MDI is based on equal weighting of the three datasets, but the weighting can change to target a particular type of drought (meteorological/short-term or hydrological/long-term). GRACE TWS is strongly correlated to long-term drought, so a heavier weight on GRACE TWS would more strongly target hydrological drought. Conversely, precipitation is strongly correlated to short-term drought, so a heavier weight on it would target meteorological drought.

The National Climatic Data Center and NOAA's Climate Prediction Center currently produce weekly maps of experimental blends of drought indicators. The first is a short-term map related to precipitation effects that occur over timespans ranging from days to months. This includes wildfire, non-irrigated agriculture, topsoil moisture, and unregulated streamflows. This value is calculated using Palmer Z-index (35%), 3-month SPI (25%), 1-month SPI (20%), CPC Soil Moisture Model (13%), and PDSI (7%) [9].

The second is a long-term map related to precipitation effects that occur over timespans ranging from several months to a few years such as reservoir stores, irrigated agriculture, groundwater levels, and well water depth. This value is calculated in the eastern portion of the US using PHDI (25%), 24-month SPI (20%), 12-month SPI (20%), 6-month SPI (15%), 60-month SPI (10%), and CPC Soil Moisture Model (10%). In the western US, the index is calculated using PHDI (30%), 60-month Average Z-index (30%), 60-month SPI (10%), 24-month SPI (10%), 12-month SPI (10%), and CPC Soil Moisture Model (10%) [9]. Figure 5.1 shows the eastern and western US boundaries [9].

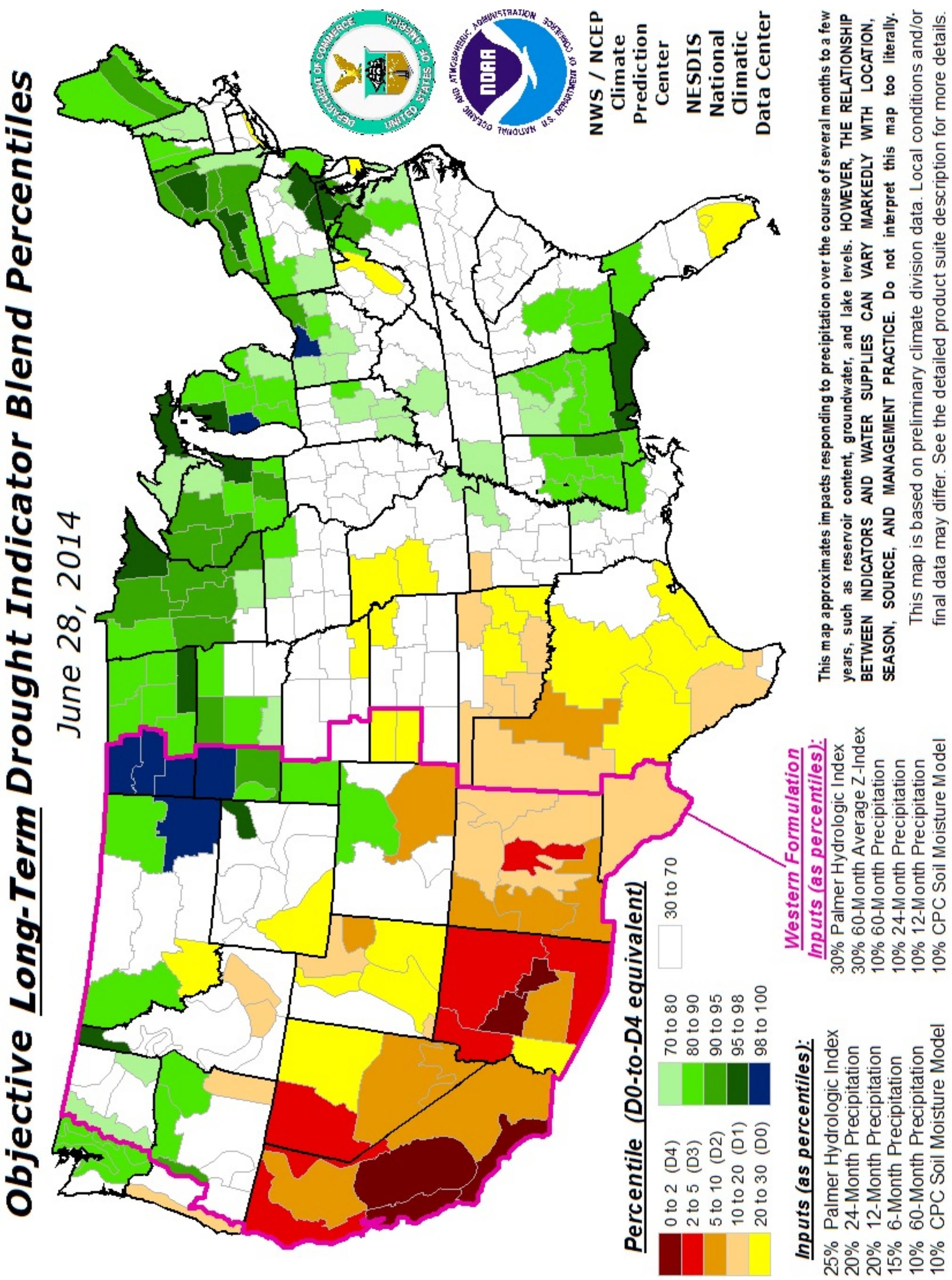

Figure 5.1: Long Term Blend Boundaries [9]

The drought index designed in this study is already a blend of datasets, and the proposed weighting scheme changes the proportion of the datasets used. The design of the signal weighting scheme is initially driven by the fact that GRACE TWS is the only dataset identifying long-term changes ranging from several months to a few years. The initial equal weighting of the datasets led to an index pre-disposed to identify shorter term events because both NDVI and precipitation are short-term datasets (datasets that identify changes ranging from days to months). To equally account for both long- and short-term changes, a preliminary weighted MDI is calculated using 50% GRACE TWS, 25% NDVI, and 25% precipitation.

The weighted MDI shows stronger correlation with PDSI in three regions: High Plains, Central Prairies, and West Gulf Coast Plains, which are all areas (excluding the West Gulf Coast Plains) with large GRACE TWS deviations. This demonstrated that a larger dependence on GRACE TWS improved the MDI's ability to identify long-term droughts, seen as a higher correlation with PDSI. An optimal weighting scheme was designed such that all regions would have improved correlations with PDSI. This method is designed to target PDSI values as "the truth", but does so by emphasizing the GRACE TWS signal. GRACE TWS has a better correlation with PDSI than precipitation does in every region, and a better correlation than NDVI does in regions with a large GRACE TWS signal such as the High Plains and Central Prairies.

The final weighting scheme given in Table 5.1 improved MDI correlation with PDSI in every region across the state, and regions with large GRACE

TWS signals (High Plains and Central Prairies) in particular. This emphasizes the importance of including GRACE TWS data, and also shows that the signal amplitude is important; regions with small GRACE TWS deviations do not have the capacity to significantly impact the results. In regions with large GRACE TWS signals, including the precipitation in the MDI calculation actually decreases the correlation with PDSI (as compared to an index based solely on GRACE TWS and NDVI). The precipitation dataset cannot be eliminated, however, because it is an important piece of information in eastern Texas (notably the West Gulf Coast Plains), which receives the most rain. Initial iterations of the weighting scheme significantly down-weighted precipitation (5%) to reduce the short-term variability of the index. This negatively impacted the West Gulf Coast Plains, however, which receive the most rain of any region in the state. Enough of the precipitation signal needed to be retained so that the West Gulf Coast still showed improvement. Note that this scheme has a nearly equal balance between long-term and short-term datasets.

Dataset	Weight
GRACE TWS	49%
NDVI	37%
Precipitation	14%

Table 5.1: Final Dataset Weights

Using this weighting scheme, the behavioral difference between MDI and PDSI improve, which is seen in monthly map comparisons presented in Chapter 5.2.1 and 5.2.2. This weighting scheme is applied across all subregions, but different weighting schemes could be adapted for different regions.

5.1.3 Robustness of GRACE TWS Signal

Of the three datasets, GRACE TWS is the least studied. To evaluate the impact of the regularized GRACE TWS solutions on MDI performance, other GRACE TWS solutions are used in the calculation of the MDI. These non-regularized solutions are produced by GFZ, JPL, and CSR. These center's solutions are available at `http://grace.jpl.nasa.gov/data/`. Each center produces a set of spherical harmonics to degree and order 60. A de-striping filter and a 300 km wide Gaussian filter are then applied to the data to minimize error [25]. Additionally, a scaling grid is available to restore the energy removed in the de-striping and smoothing process [25]. The scaling coefficients were derived by applying the same filters to a numerical land-hydrology model (NCAR's CLM4) [25]. For comparison purposes, there are six datasets: a scaled and unscaled set from each data center.

The unconstrained GRACE TWS solutions are used with the same NDVI and precipitation datasets to calculate MDI. Correlation coefficients for the new GRACE TWS datasets and drought indices (MDI, WVI, TWI) with PDSI are calculated. The results are given in Table 5.2 through Table 5.7.

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.73	0.80	0.72	0.68	0.69
WVI	0.88	0.90	0.83	0.87	0.83
TWI	0.84	0.85	0.83	0.82	0.82
MDI	0.90	0.90	0.86	0.89	0.87

Table 5.2: CSR Tellus Data (Scaled) - PDSI Correlation Coefficients

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.73	0.79	0.72	0.67	0.69
WVI	0.88	0.89	0.83	0.86	0.83
TWI	0.84	0.84	0.82	0.82	0.82
MDI	0.90	0.89	0.86	0.89	0.87

Table 5.3: CSR Tellus Data (Un-scaled) - PDSI Correlation Coefficients

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.75	0.82	0.70	0.61	0.58
WVI	0.88	0.90	0.82	0.83	0.77
TWI	0.85	0.86	0.81	0.80	0.78
MDI	0.91	0.90	0.85	0.88	0.84

Table 5.4: JPL Tellus Data (Scaled) - PDSI Correlation Coefficients

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.75	0.81	0.70	0.61	0.59
WVI	0.88	0.90	0.82	0.83	0.78
TWI	0.85	0.86	0.81	0.80	0.78
MDI	0.91	0.90	0.85	0.88	0.84

Table 5.5: JPL Tellus Data (Un-scaled) - PDSI Correlation Coefficients

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.71	0.76	0.70	0.66	0.66
WVI	0.87	0.88	0.83	0.86	0.84
TWI	0.84	0.84	0.81	0.82	0.80
MDI	0.91	0.90	0.85	0.89	0.87

Table 5.6: GFZ Tellus Data (Scaled) - PDSI Correlation Coefficients

Dataset	CD	HP	CP	STP	WGC
GRACE TWS	0.71	0.75	0.70	0.66	0.67
WVI	0.87	0.88	0.83	0.86	0.84
TWI	0.84	0.84	0.81	0.82	0.81
MDI	0.90	0.89	0.85	0.89	0.87

Table 5.7: GFZ Tellus Data (Un-scaled) - PDSI Correlation Coefficients

From these results, the percent change can be calculated. The largest correlation coefficient change is the GRACE TWS signal itself. For every solution, the largest changes occur in the West Gulf Coast Plain (ranging from 13% to 24%), and very little change occurs in the Chihuahuan Desert (0.6% to 5%). The small change in the Desert is likely related to the low-amplitude signal in that area. The West Gulf Plains region is not particularly large, but it does have more variability in water storage. Though there is change in the GRACE TWS signal, it does not meaningfully change the correlation of MDI with PDSI (the average percent change across all regions is 1.4%). This demonstrates that the methods used in this study are not dependent on a particular type of GRACE TWS input, lending robustness to the solution. This study also shows that if the GRACE TWS signal amplitude changes, it does not negatively impact the MDI, as deviations of the signal are used in the calculation. In the future, a more thorough test will be drought identification and classification using these new GRACE TWS inputs.

5.2 Specific Drought Events

Analysis of two events in particular help assess MDI behavior. A period of excessive moisture (2007) and a period of extreme dryness (2011 Water Year) represent the extremes of the time period studied (2002 - 2014) and illustrate the limits of MDI.

5.2.1 2007 Moisture Event

2007 was an anomalous year because of the heavy amount of rain Texas received. Both the weighted and unweighted MDI correlated with PDSI better than the individual datasets. Of the datasets, however, GRACE TWS has a stronger correlation to PDSI in the High Plains and West Gulf Coast Plains. Across the state, the GRACE TWS and NDVI behavior agrees with the weighted and unweighted MDI behavior, but precipitation is much more variable (it is a short-term signal). Because two of the three datasets agree, the weighting scheme does not significantly impact the MDI behavior. Any changes between the weighted MDI and the unweighted MDI are related to the variations in precipitation, with the exception of changes in September 2007 onward in the Chihuahaun Desert. In this instance, GRACE TWS shows a large positive deviation, presumably due to the accumulation of months of excessive rain. This large GRACE TWS deviation is likely the contributing factor to a larger weighted MDI.

The peak magnitude occurred in July. The monthly maps of MDI, weighted MDI, and PDSI all reasonably agree. These maps, respectively, are shown in Figure 5.2 through Figure 5.4. Figure 5.4 is generated by NOAA and provides the drought state for the conterminous United States [9]. The weighted MDI shows the High Plains shift from W2 classification to W3 and the Chihuahuan Desert shifts from W1 to W2 classification. The Central

Prairies, South Texas Plains, and West Gulf Coast Plains shift from W4 to W3 classification. The weighted MDI map more closely matches the PDSI map, which was the intent of the weighting scheme.

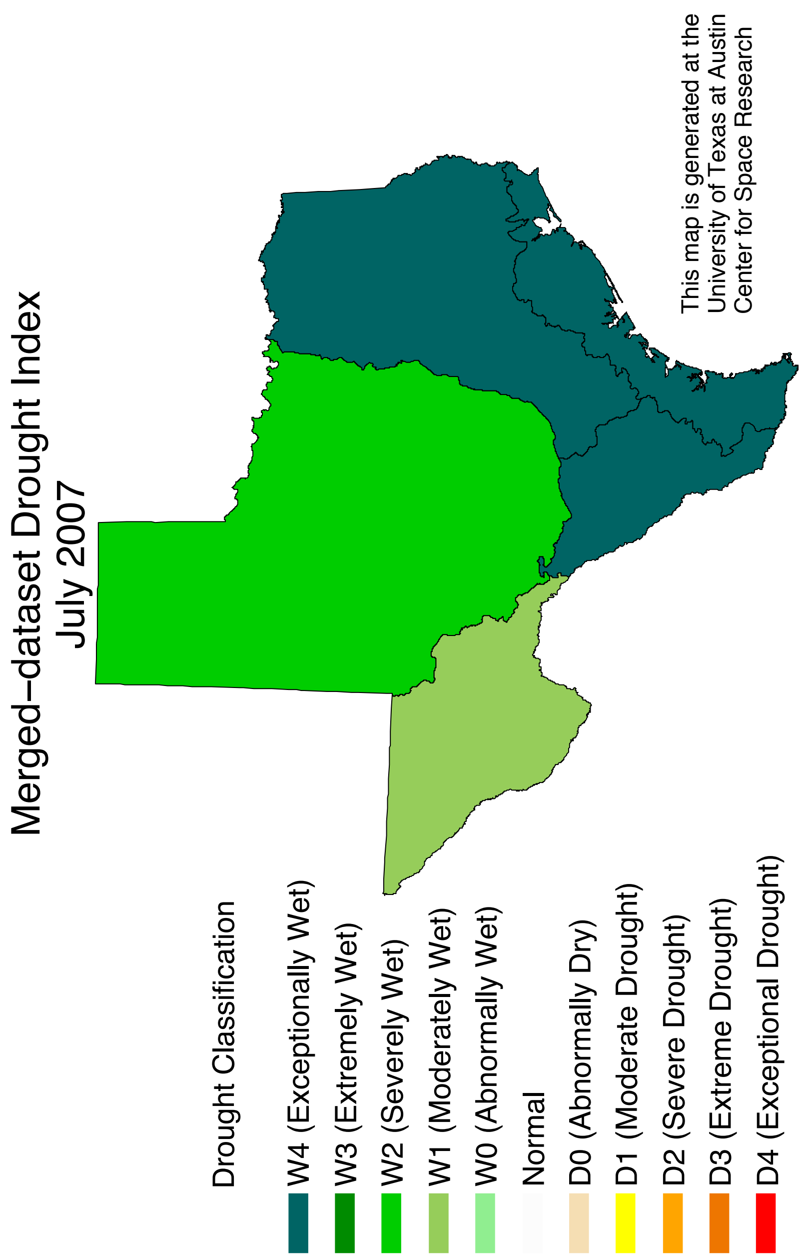

Figure 5.2: July 2007 MDI Monthly Map

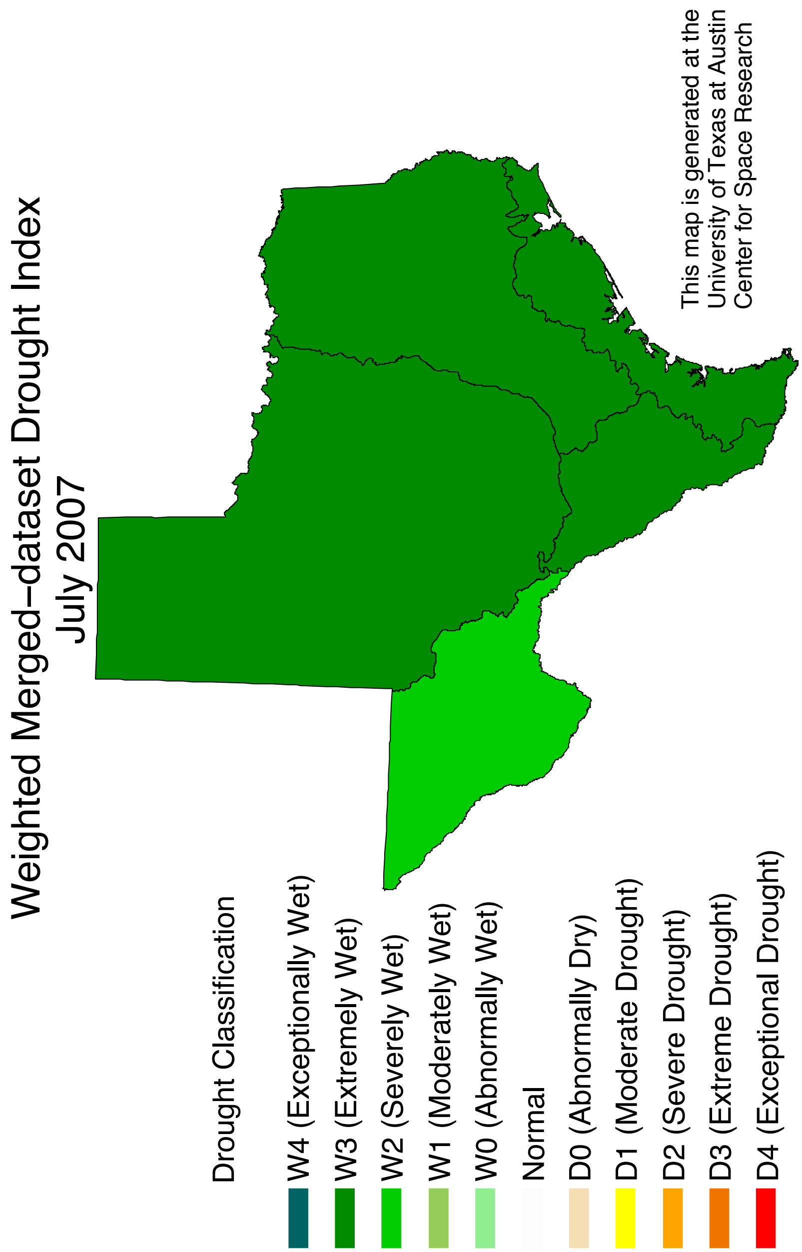

Figure 5.3: July 2007 Weighted MDI Monthly Map

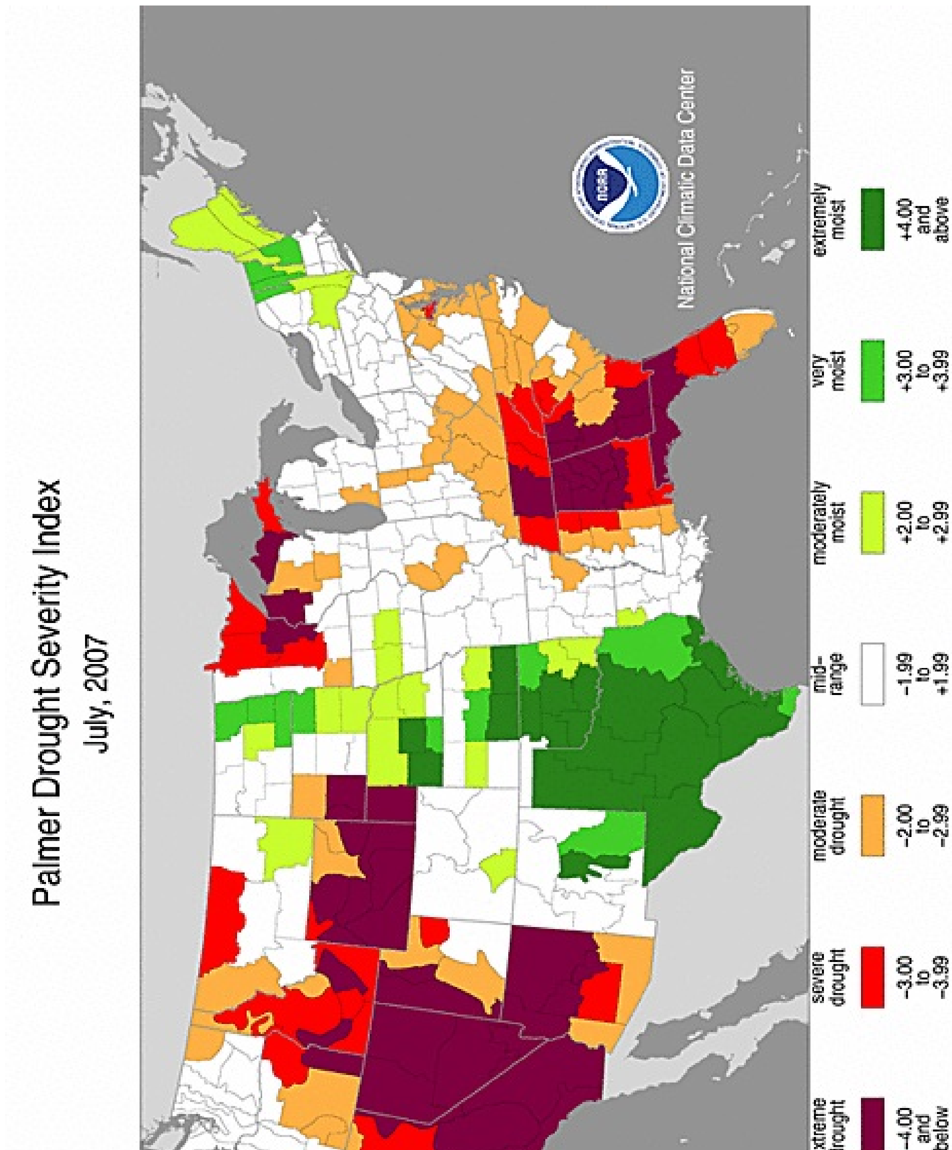

Figure 5.4: July 2007 PDSI Monthly Map [9]

5.2.2 Water Year 2011 Drought

The 2011 Water Year lasted from October 2010 to September 2011, which is the same time as one of the worst droughts in Texas history. The drought peaked in September 2011. The monthly maps of MDI, weighted MDI, and PDSI all reasonably agree. These maps, respectively, are shown in Figure 5.5 through Figure 5.7. These images show that the weighted MDI does not change any region classification, and based on the MDI, 70% of Texas is in exceptional drought, while the remainder is in extreme drought. PDSI classifies all of Texas in extreme drought, which supports the MDI classification.

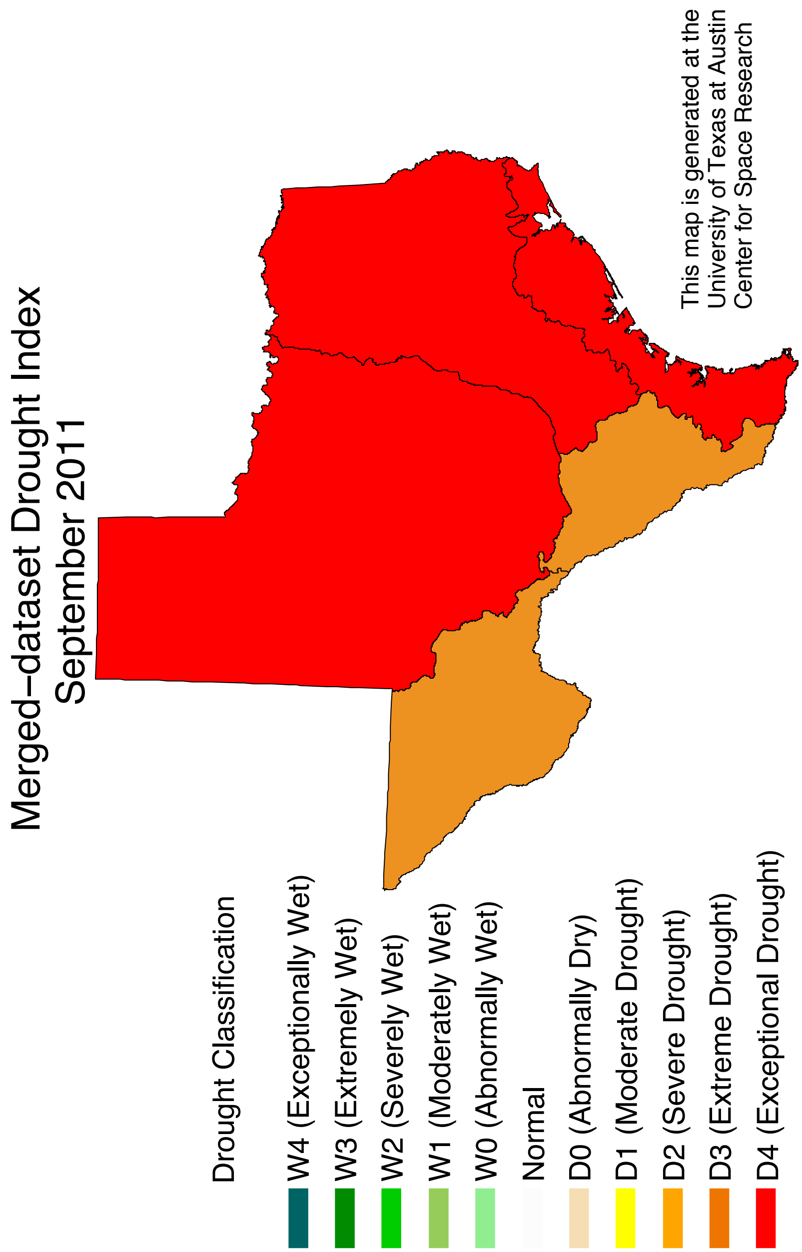

Figure 5.5: September 2011 MDI Monthly Map

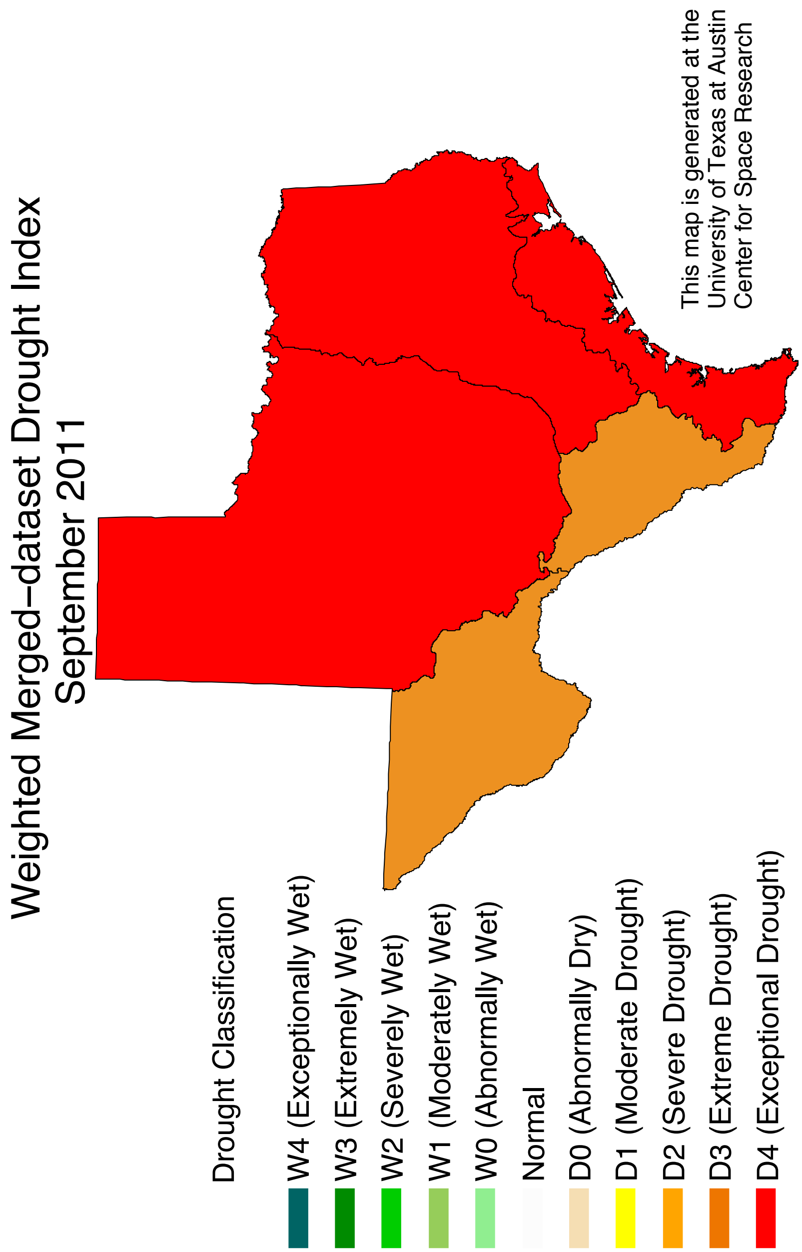

Figure 5.6: September 2011 Weighted MDI Monthly Map

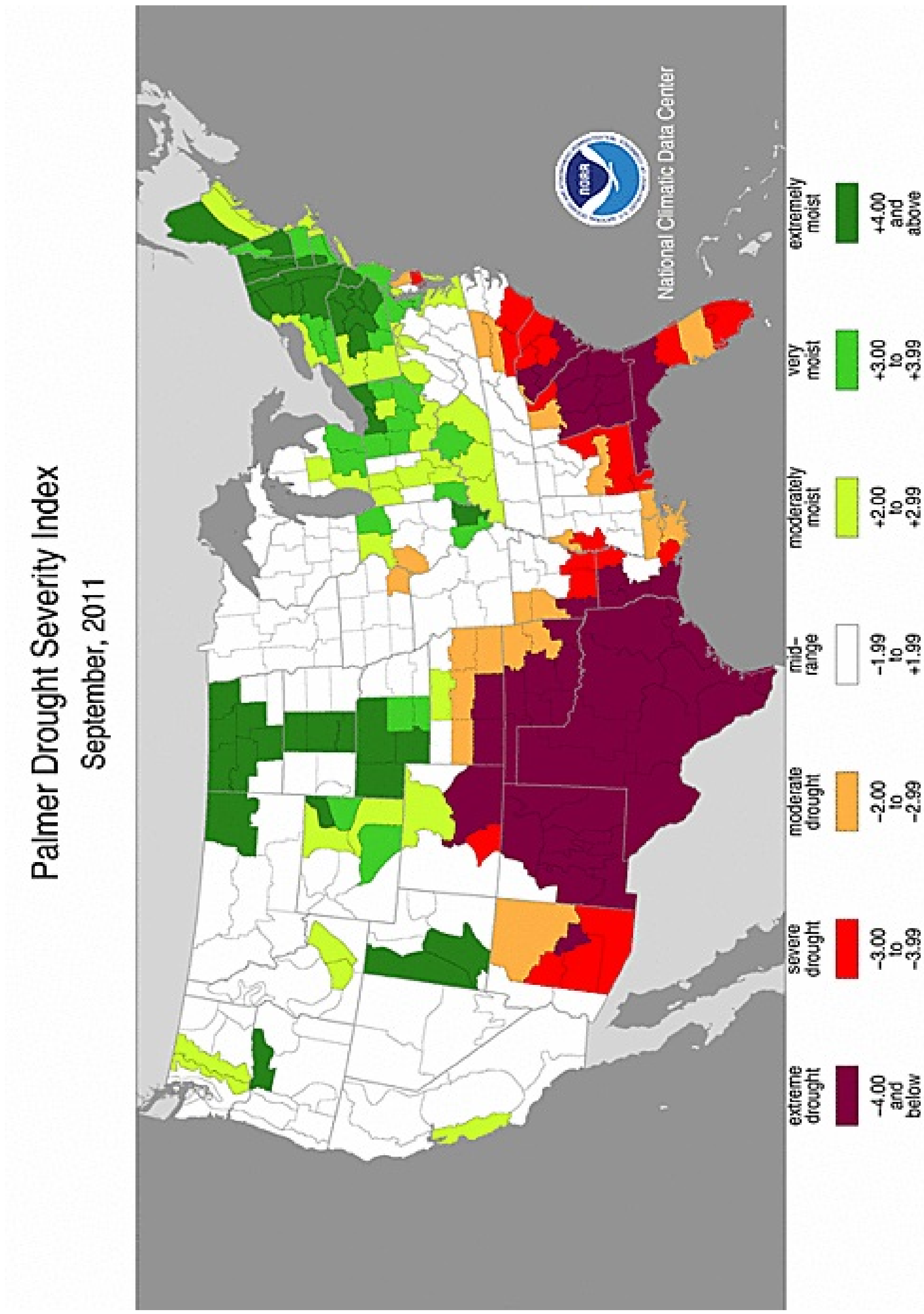

Figure 5.7: September 2011 PDSI Monthly Map [9]

5.2.3 December 2011 Anomaly

An interesting behavioral deviation occurred in December 2011, specifically in the Central Prairies. The calculated MDI was 0.48 (Class M0) while the calculated PDSI was -5.0 (Class D4). Examination of the datasets showed large positive deviations in NDVI and precipitation, and a negative GRACE TWS deviation. October and November recorded heavier than normal rainfall, which could explain the "Abnormally Wet" conditions the Central Prairies experienced according to the MDI. Though the MDI and the PDSI do not agree in this month, both are accurate portrayals of the conditions experienced in the Central Prairies. A warmer than usual winter may also contribute to drought conditions, which PDSI would acknowledge while MDI would not.

The heavy rainfall from previous months helped revive vegetation response, and continued heavy rainfall in December could explain the positive deviation in those two datasets. These deviations drown out the negative GRACE TWS deviation, which is the only signal to identify the region as being in drought. Considering that the region had been in drought over a year by December 2011, it is not surprising that water storage remains deficient. Though surface responses reveal a return to normal behavior, GRACE TWS lags behind. The weighted MDI does not identify any regions as wet, and the West Gulf Plains are categorized as Class D0, but the weighted MDI still does not identify the state as being in widespread extreme drought as the PDSI does. In this instance, the heavier weighting of GRACE TWS is not enough to completely correlate MDI with PDSI, but it does improve MDI performance.

The most recent MDI data used in this study was January 2014, and at that time, the MDI identified all regions except the South Texas Plains as being in a slightly more severe drought than the PDSI.

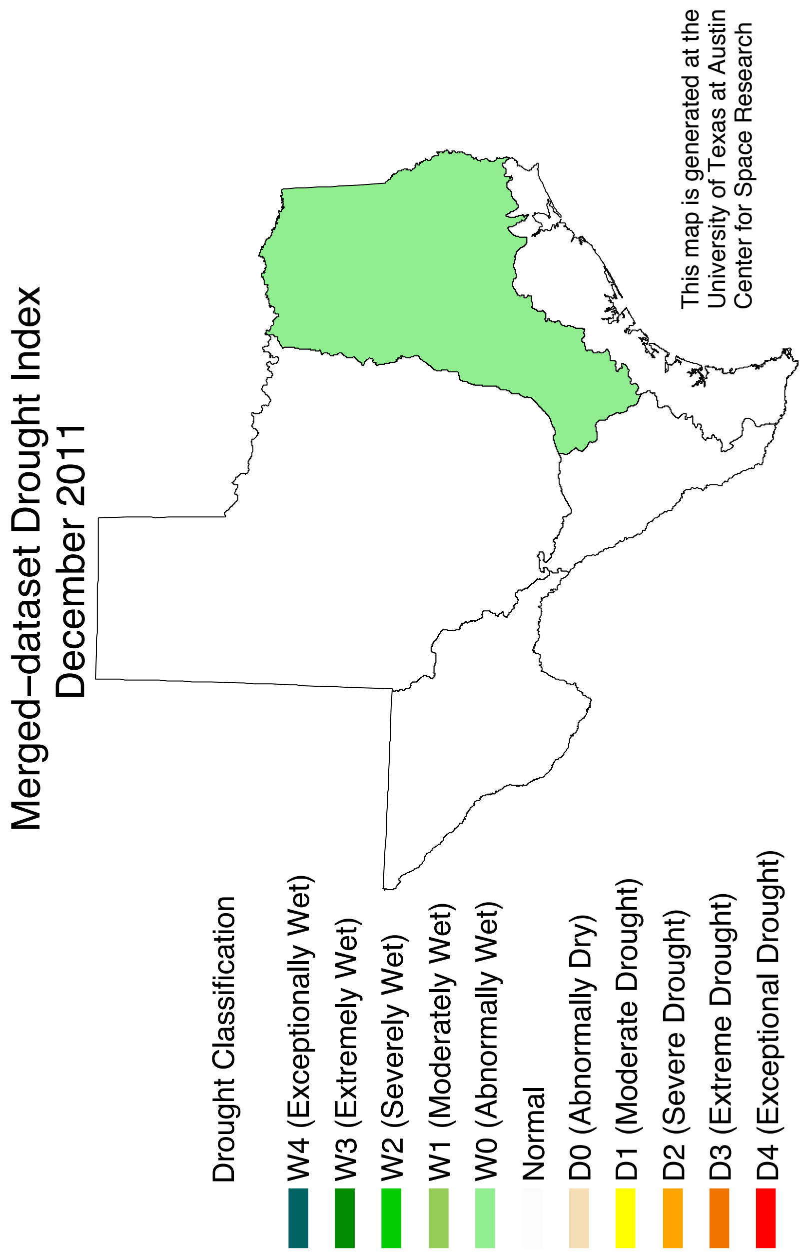

Figure 5.8: December 2011 MDI Monthly Map

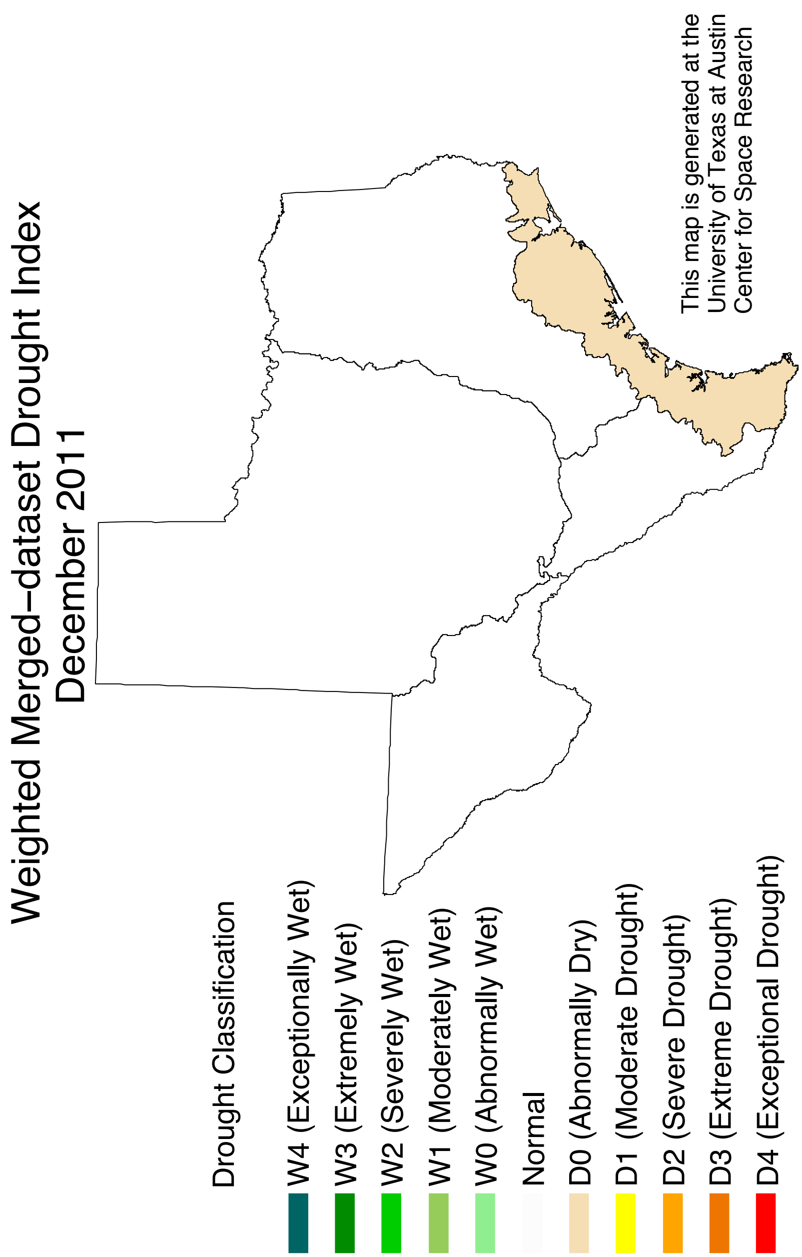

Figure 5.9: December 2011 Weighted MDI Monthly Map

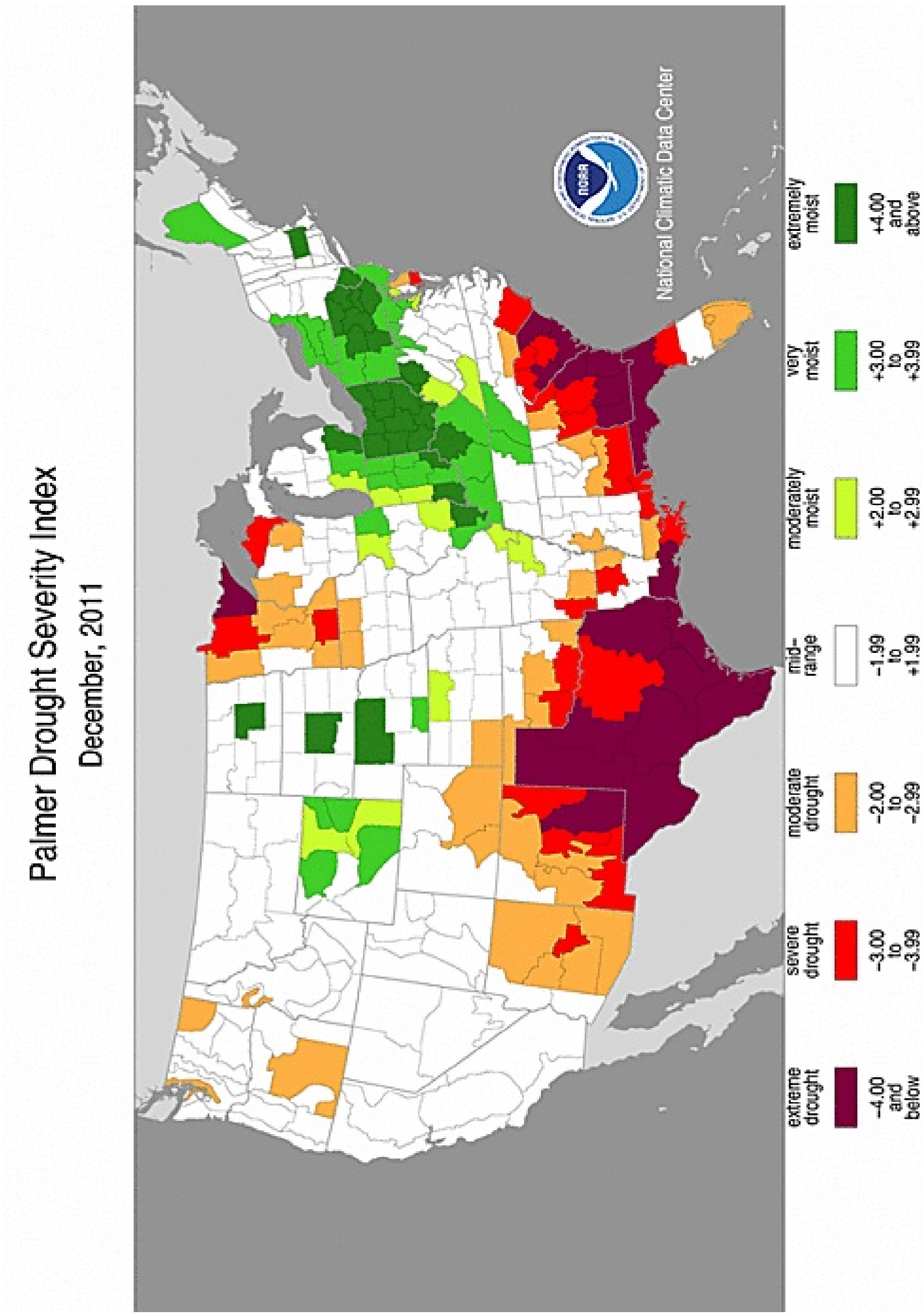

Figure 5.10: December 2011 PDSI Monthly Map [9]

5.2.4 Dataset Requirements for Drought Identification

The events discussed in Chapter 5.2.1 and 5.2.2 are extreme events with large magnitude MDI values. These events do not suffer from rapid fluctuations in MDI values that indicate event reprieves that may or may not exist. These fluctuations are more common in less severe events.

A drought event is identified in a region when the MDI is negative for a minimum of three consecutive months. This coincides with the length of a season, but is also based on the results of the dataset - drought index correlation study. That study found that in Texas, precipitation correlates most strongly with 1-Month SPI and Palmer Z-index, NDVI correlates most strongly with PDSI, PMDI, and 6-Month SPI, and GRACE TWS correlates most strongly with PHDI, PMDI, and 12-Month SPI. Considering these results, this study defines the threshold for meteorological drought as three months, the threshold for agricultural drought as six months, and the threshold for hydrological drought as nine months. The US Drought Monitor, while not as explicit, has a similar time requirement: events shorter than 6 months are short-term (ST) events, and events longer than 6 months are long-term (LT) events. Considering these thresholds, an MDI deficiency must persist for at least three months to label that time period as being in drought. The magnitude of the deficiency does not matter–any sustained deficiency will flag a drought event. To classify a drought event as TS0 (the first severity class), the event's total severity must exceed a magnitude of 0.8. Since the total severity calculation depends on the region's area, determining the minimum MDI size needed for drought identification is much more challenging.

Calculating reprieve from drought is also challenging. Reprieve is used in this context as the time period between two droughts, and is defined by a positive MDI for three consecutive months. If this criteria is not met, two drought events are merged into a single event as in Chapter 4.4. In addition to duration, the magnitude of the index should be considered. For example, in the Central Prairies from October 2010 to September 2013, there is a reprieve from December 2011 through March 2012. This reprieve lasts 4 months, so the duration test is passed. The magnitude is a little trickier, as the peak positive MDI during this time is 1.61. As previously described, however, this rise is due to significant positive deviations in NDVI and precipitation. GRACE TWS remains negative, as does the PDSI. With these pieces of information, it becomes harder to determine what is actually going on. In the High Plains, there is a four month reprieve between two events that lasts from December 2011 to March 2012 as well. The peak MDI during the reprieve, however, is only 0.53. This is 1/3 the size of the peak in the Central Prairies. GRACE TWS deviations and PDSI are both negative during this four month period in the High Plains as well.

Considering the drought classification scheme, the peak reprieve value of 1.61 in the Central Prairies is "Severely Moist", and the peak value of 0.53 in the High Plains is "Abnormally Moist". Another piece of information to consider is the weighted MDI value. In the Central Prairies, the weighted MDI records drought from October 2010 to January 2014 with two reprieves: one from December 2011 to April 2012 (peak MDI = 1.18 in March) and a second from October to December 2013 (peak MDI = 0.22 in December). In the High

Plains, the weighted MDI measures a one-month reprieve in March 2012 (MDI = 0.37). This is "Moderately Moist" and remains a severe difference from the PDSI value and GRACE TWS deviation. Considering the MDI magnitude, negative GRACE TWS deviations, negative PDSI values, and shorter and less severe reprieves according to weighted MDI, the reprieve in the High Plains is insufficient to separate drought events (it is artificial), but the reprieve in the Central Prairies is enough for separate classifications (it is genuine). This study reveals the complexities associated with reprieve classification.

5.3 GRACE Contributions to MDI

GRACE TWS is the only dataset to provide long term water storage information. Both NDVI and precipitation provide information on the weekly to monthly scale, but short-term changes ignore the long-term impact of shortages in water. GRACE TWS accounts for "pre-conditioning" from past months of excessive or deficient water, which is more difficult for NDVI to maintain and impossible for precipitation measurements, which are event based, to capture.

In regions with adequate signal amplitude (i.e. the High Plains), GRACE TWS has the strongest correlation with PDSI. GRACE TWS correlates most strongly with PDSI in the West Gulf Coast Plains as well. This is more surprising as the GRACE TWS signal size here is much smaller than in the High Plains. The signal is approximately the same size as that of the Chihuahuan Desert or South Texas Plains, two regions in which NDVI has the strongest correlation with PDSI. These two regions' correlations with NDVI is also surprising because of the lack of vegetation in the regions. The Chihuahuan Desert in particular has an extremely small vegetation signal, so its correlation with PDSI is questionable. Overall, GRACE TWS has a stronger correlation with PDSI than precipitation.

The developed weighting scheme also highlights the importance of the GRACE TWS data. When GRACE TWS is weighted more heavily, the significant behavioral differences between MDI and PDSI (notably in December 2011) are reduced. For the most recent drought, GRACE TWS is the only dataset that continues to show negative deviations after drought onset (October 2010) to January 2014. This suggests that for Texas, as droughts become more severe, GRACE TWS is more suited than NDVI or precipitation to identify drought.

One of the limitations previously addressed is vegetation senescence. There may be artificial deviations in winter months that influence MDI in inappropriate ways (i.e. positive NDVI deviations inflate MDI, as in December 2011). GRACE TWS does not have this limitation.

GRACE TWS is also the only dataset used in this study that accounts for water storage below ground. NDVI accounts for water storage on the surface (as manifested by plant growth), and precipitation accounts for water input to the surface. Accounting for water storage below ground is important because it provides temporally and spatially consistent data that is historically very hard to collect. This then allows researchers and policy makers to make more educated decisions. In-situ data from soil moisture gages, streamflow gages, etc. is not available consistently across the state and is also not available at the same temporal frequencies or the same temporal ranges. TWS measurements from the GRACE satellites corrects these problems. Seeing below ground causes GRACE to extend the duration of a drought, accounting for the time it takes the hydrological system to completely recover.

In the High Plains, for example, there is a strong GRACE TWS signal. NDVI identifies a drought from November 2008 to April 2009. That the majority of this event is during the winter when there is little vegetation signal calls this event into question, but it is even more interesting that NDVI does not identify drought after April 2009. This is likely due to heavy rainfall that ends the drought at the surface level. GRACE TWS, however, identifies a drought from December 2008 to October 2009. This demonstrates the "pre-condition" phenomenon in that the shortage of water in early 2009 takes longer to recover, and so the drought lasts past April. MDI identifies a drought from September 2008 to June 2009, showing that the influence of GRACE TWS extends the drought past the NDVI end date. Precipitation only showed a drought from November 2008 to February 2009. It is likely the shortage of rainfall negatively impacted NDVI, but this short meteorological drought results in a quicker NDVI recovery and a longer GRACE TWS recovery.

Another example in the High Plains is the drought that began in October 2010. GRACE TWS identifies one drought from September 2010 to January 2014, showing that the system has suffered severe water shortages and has not yet recovered. NDVI shows two droughts, one from September 2010 to December 2011 and a second one from May 2012 to September 2013, while precipitation identifies four droughts: October 2010 to September 2011, April 2012 to August 2012, October 2012 to December 2012, and February 2013 to June 2013. MDI identifies two droughts: October 2010 to November 2011 and April 2012 to January 2014. This demonstrates the importance of including long-term information, such as GRACE TWS. The short-term meteorological droughts identified by precipitation do not consider the cumulative effect of lack of moisture, which is critical for determining the drought duration and severity. NDVI does a better job of accounting for this, but GRACE TWS is best.

Similar phenomena occur in the Central Prairies. GRACE TWS identifies one drought from September 2010 to January 2014, NDVI identifies three separate droughts, and precipitation identifies only one drought from October 2010 to November 2011. MDI identifies two droughts, October 2010 to November 2011 and April 2012 to September 2013. This is another example of GRACE TWS accounting for long-term recovery time and influencing the MDI. The weighting scheme introduced in Chapter 5.1.2 further improves this. Based on examples in the High Plains and Central Prairies, the GRACE TWS-identified droughts are not broken up by artificial 1-2 month reprieves. These long-term events are impacted by multiple short-term events, which are aggregated into single droughts.

Chapter 6

Conclusion and Recommendations

6.1 Conclusion

This study successfully demonstrates GRACE TWS, NDVI, and precipitation data can be fused together to create a new drought index. Each dataset was selected because it related to a different type of drought. GRACE TWS provides an integrated measure of water storage that considers surface and subsurface storage, which lends GRACE TWS to hydrological drought monitoring. NDVI measures the level of photosynthetic activity and evaluates vegetation health. NDVI is more suited to identify agricultural drought. Precipitation measures water input to an area. Precipitation events can have relatively immediate impacts and are useful for meteorological drought monitoring.

A correlation study is performed to identify sub-regions within Texas. Five regions are created for which the GRACE TWS, NDVI, and precipitation behaviors are distinct. Regions in East Texas receive more precipitation, have more consistently dense vegetation, and abundant water storage. West Texas receives little precipitation, has sparse vegetation, and diminished water storage capacity. The datasets in West Texas (i.e. the Chihuahuan Desert) are all low-amplitude signals, so the author is less confident in the results for those regions.

A monthly climatology is defined for each dataset for the time period of interest, and deviations from that normal are calculated. These deviations are converted to z-scores used to calculate the Merged-dataset Drought Index. This calculation method is not specific to a particular region, and it is also simple to perform and easy to understand. MDI is calculated on a monthly basis for every region. MDI's strong correlation with current drought indices (such as PDSI, PHDI etc.) demonstrates that it identifies droughts in a manner consistent with current practices. MDI is simpler to calculate than PDSI, and provides the same information, making MDI a viable index for regions where PDSI is not available. A new drought classification scheme based on MDI is proposed. This scheme is created based on the regional Texas results, and can be improved with a longer data record. To integrate with current practices, the scheme has classes ranging from D4 to D0 with characteristics matching that of the US Drought Monitor Classification Scheme. This drought severity scheme categorizes each monthly MDI value, regardless of whether or not a region is in drought.

MDI successfully identified multiple droughts from 2002 - 2014 in every region of the state. Identified droughts generally occurred in the same timespan across the regions, though the impact of the drought on the ecosystem varied. A drought event is identified when the MDI is negative for a minimum of three consecutive months. The most severe drought began in October 2010. The state has yet to recover. MDI also identifies reprieves between drought events. Criteria are developed to evaluate if the reprieve is genuine or an artifact of an artificially inflated data signal. One criterion is reprieve duration, which must exceed three months. Two separate drought events in the South Texas Plains, separated by a two-month reprieve, are merged because the reprieve does not meet this duration criterion. A similar fusion of drought events occurs in the West Gulf Coast Plain, where two drought events are also separated by a two-month reprieve.

Based on the identified drought events, a total severity (TS) classification scheme is also proposed. This scheme differs from the drought severity scheme because the TS scheme is multi-month and only applicable once a drought has been identified. The TS scheme considers area affected, which the drought severity scheme does not, and total severity can be calculated on a rolling basis. To classify a drought event in the mildest severity category (TS0), the event's total severity must exceed a magnitude of 0.8. Since total severity depends on a region's area, defining a minimum cumulative MDI value for drought is more challenging.

This index is limited by the spatial resolution of the GRACE TWS input dataset, which guides the regional division of Texas. The spatial resolution of GRACE TWS is constrained by the accuracy of the range measurements between the GRACE satellites and their height above the Earth. To operate at the county level, which current drought indices are able to do, the GRACE TWS spatial resolution needs to improve an order of magnitude. This serves as a baseline for the necessary spatial resolution required from future geodetic space missions for use in drought identification at smaller scales.

A weighting scheme is also introduced to improve MDI performance. The scheme is designed to improve MDI - PDSI correlation in every region across the state, leading to a weighting using 49% GRACE TWS, 37% NDVI, and 14% precipitation. This scheme results in an MDI that equally accounts for long-term hydrological indicators and short-term meteorological indicators. The GRACE TWS dataset is also the least mature dataset used in this analysis. Unconstrained GRACE solutions are available, both from CSR and other GRACE processing centers, and these solutions are used in place of the regularized CSR solution to evaluate GRACE TWS impact on MDI. Depending on the input, the MDI - PDSI correlation varies, but no more than 1.4%. This demonstrates that the signal size is less important than the signal variation in this study.

MDI has superior performance in areas with larger-amplitude GRACE TWS signals such as the High Plains and Central Prairies, especially when the weighted MDI is considered. Other regions, such as the Chihuahaun Desert and South Texas Plains have small geographical areas and small GRACE TWS signals, which hinder MDI performance.

Two specific events are addressed to more thoroughly evaluate MDI performance. Beginning in late spring 2007, Texas received excessive amounts of rain. The peak occurred in July 2007, and at this time, the MDI, weighted MDI, and PDSI all showed similar classifications across the state. One of the worst droughts in Texas history occurred during the 2011 Water Year, and the drought peaked in September 2011. During this month, MDI, weighted MDI, and PDSI all identified regions in Texas as being in extreme or exceptional drought. MDI behavior departs from PDSI behavior during the 2011 winter months when MDI records normal to wet conditions while PDSI still records exceptional drought conditions. This is likely due to heavy rains in late 2011 which immediately impact MDI through positive precipitation and NDVI deviations.

GRACE TWS is particularly important to MDI formulation because it is the only dataset to provide long-term water storage information. It accounts for "pre-conditioning" from past months of excessive or deficient water, which NDVI and precipitation are less suited to do. Incorporating GRACE TWS into MDI formulation reduces the artificial reprieves from a drought and merges multiple short-term events into single long-term events. GRACE TWS is also not affected by senescence, a phenomenon that limits the use of vegetation.

6.2 Recommendations

A longer data record is particularly important for refining the drought and total severity classification schemes. Future geodetic missions will have improved spatial resolution, which will enable finer sub-division of Texas and help highlight more regional differences that may currently be masked. The baseline established in this study can help guide requirements for these future missions. In lieu of new data, assimilating GRACE TWS data into a Land Surface Model is a valid way of potentially gaining finer resolution TWS data.

This study lays the groundwork for a future, completely remote-sensing based index. Precipitation is the only in-situ dataset, but the launch of the

Global Precipitation Measurement satellite mission [35] enables satellite-based precipitation measurements. All three datasets would then be available on a temporally and spatially consistent basis around the globe, enabling MDI calculation everywhere, especially in regions that historically are hard to measure and evaluate.

No drought index, including MDI, is completely able to identify all facets of drought. MDI robustness may be enhanced, however, through the addition of other datasets. Temperature, for example, plays an important role in atmospheric interactions and land surface temperature has historically been used in drought index formulations. Even with the abundant methods available to identify drought, predicting drought is much more complex. Further investigations into the capability of MDI to predict drought would be beneficial.

Appendix

Appendix A

GRACE Pixel Organization

This map depicts the final pixel organization used in the region aggregation. Each square denotes a 1° by 1° pixel, and the yellow outlines denotes the EPA Level III organization. If a pixel is part of multiple regions, the region with a larger area accumulates the pixel. Each pixel is therefore only part of one region.

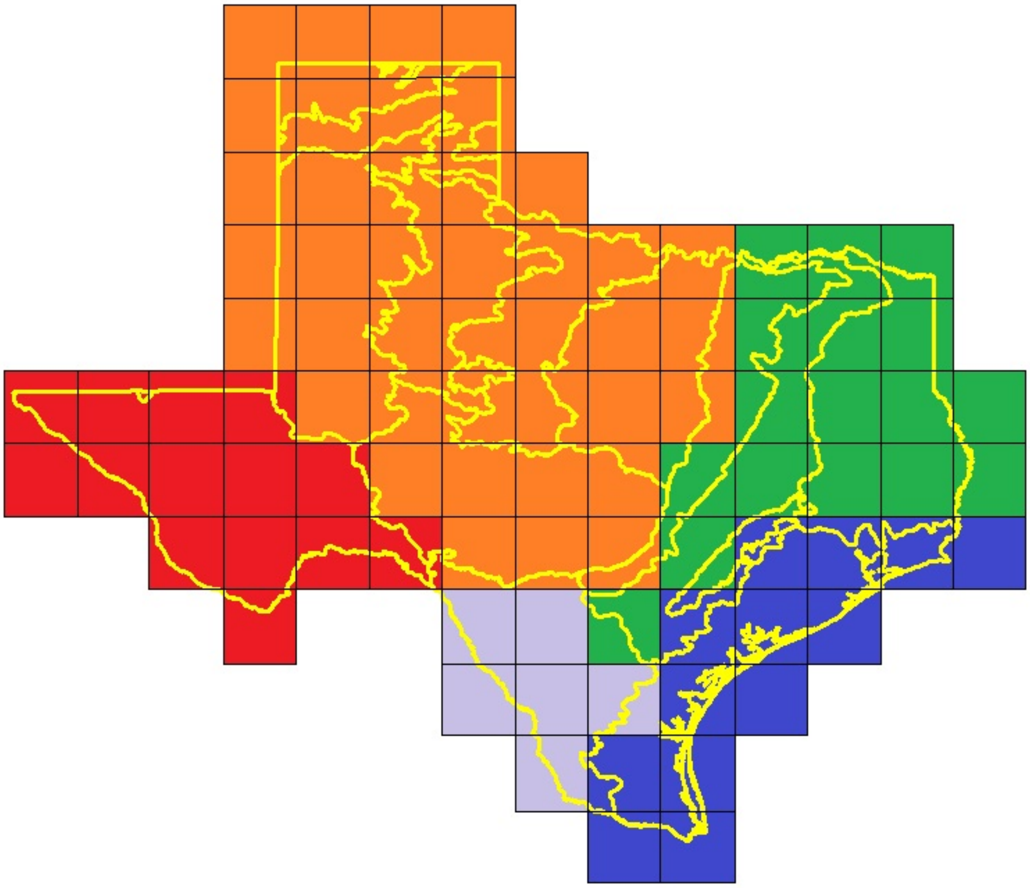

Figure A.1: Pixel Organization

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